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From Micro to Macro in an Equilibrium Diffusion Model*

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Abstract

We quantify the benefits of better firm-to-firm matching in an aggregate diffusion model where individuals reap profitable knowledge from others in the economy. We estimate the model using a recent empirical evaluation of a small-scale program in Kenya that creates new opportunities for firm managers to interact. Critical to the aggregate gains from the program is the relative importance of meeting a high-knowledge firm compared to the learning that happens within that meeting. We show how moments from the intervention identify these diffusion parameters. Doing so formalizes how other easily-estimated moments besides the average treatment effect provide crucial information about at-scale gains. We lastly provide sufficient conditions under which the same identification procedure holds for a wider class of experiments and aggregate diffusion models that covers much recent work.

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1 Introduction

One of the fundamental constraints to economic development is limited managerial capacity. Despite the ubiquity of small firms in developing countries, many have low profit and few workers. Billions of dollars are spent attempting to correct these skill deficiencies (Blattman and Ralston, 2017). While many solutions have been proposed, a flurry of recent micro-level interventions have highlighted one promising channel: learning from others. The premise of these interventions is that frictions limit interactions with more skilled or knowledgeable firms, which lowers managerial capacity and thus firm growth. Facilitating meetings between firm managers, and thus overcoming these frictions, would therefore be beneficial. Results from several studies support this view, and show that interventions encouraging learning from other managers increase profit, technology adoption, and managerial skills.[1]

Yet the general equilibrium, at-scale implications of these interventions are less explored, and there are reasons to suspect they may differ from what can be extrapolated directly from these treatment effects. First, general equilibrium forces can complicate the link from treatment effects to at-scale outcomes (Buera et al., 2022). Here, this takes the form of knowledge spillovers. When the knowledge created in these interventions can further permeate the economy through diffusion, the aggregate gains from better matching will depend on changes to the entire distribution of knowledge (Lucas and Moll, 2014; Perla and Tonetti, 2014). Second, the benefits of making it easier to meet high-knowledge agents will depend on different factors. How hard is it to meeting these agents without an intervention? How much can be learned once those meetings do occur? If these "meeting" and "learning" technologies have different contributions to aggregate outcomes, it opens up the possibility that the same treatment effect is consistent with a variety of aggregate outcomes.

Our contribution in this paper is two-fold. We formalize the link between experimental moments and elements of the of the diffusion process in a general equilibrium model of firm-to-firm diffusion. Specifically, these moments provide a natural way to separate the relative importance of meeting and learning technologies. We then show that doing so matters quantitatively both for understanding aggregate implications and for interpreting reduced-form moments as measures of at-scale potential.

We focus our discussion around the results of a randomized controlled trial in

[1]There now exists a broad set of interventions that are designed to give firms access to new information embedded in other economic agents. Cai and Szeidl (2018) create randomly-formed business groups in China. Brooks et al. (2018) and Lafortune et al. (2018) create random one-to-one matches among Kenyan and Chilean microenterprise owners. Fafchamps and Quinn (2018) introduce smaller-scale firm owners to managers of high-profit firms in Ethiopia, Tanzania, and Zambia. Relatedly, Atkin et al. (2017) introduce random variation in buyer-seller links in Egypt and Beaman et al. (2021) randomly seed information on new technology in Malawi. See also Giorcelli (2019) and Bianchi and Giorcelli (2022) for historical examples of firm-to-firm knowledge transfers and Munshi (2008) and Breza et al. (2019) for reviews.

Kenya (Brooks et al., 2018), though as we will discuss at length later, many of the insights can be formally generalized to a class of models and interventions that cover a larger body of recent work. In this RCT, we randomly paired high- and low-profit female business owners in Nairobi, Kenya. There are three main findings. First, average profit rose by 19 percent for the less-profitable member of the match, with no statistically significant change for the more profitable business owner. Second, the treatment effect is largest among those who are randomly paired with higher-profit matches. Third, the underlying mechanisms are primarily on the cost side: treated owners were more likely to switch suppliers and their costs declined significantly.

Our RCT, like those cited above, focused on the direct effect for those engaged in a match. Offering the same intervention at scale requires taking into account how knowledge diffusion perpetuates those individual-level gains. We therefore build a general equilibrium model of knowledge diffusion to discipline this process. While adopted to the specifics of our settings, the basic structure shares much with standard models in the literature (as reviewed in Alvarez et al., 2008; Buera and Lucas, 2018). Individuals choose whether to run a firm or work at one. Their entrepreneurial income depends in part on knowledge of the market. Knowledge here represents the ability to more easily seek out low cost suppliers, consistent with our empirics. The diffusion of that knowledge results from random interactions: agents can increase their own knowledge by interacting with other firm operators, as long as those other owners are sufficiently knowledgeable. This process depends on two technologies, *meeting* and *learning*. Meeting determines the likelihood of meeting another agent with high knowledge. The learning technology controls how much knowledge can be extracted from a given meeting. Taken together, the model formalizes an equilibrium relationship between economic decisions made by agents, the technology that translates these meetings into profitable knowledge, and the potential set of opportunities agents face.

Our main quantitative exercise asks how average income changes when it becomes easier to meet high knowledge agents. The goal of this exercise is to replicate the same idea as the RCT but use the model to account for the additional equilibrium gains created by the diffusion of that knowledge. We implement it by shocking the meeting technology, changing the relevant parameter by 25 percent. For a rough sense of magnitude, this increases the knowledge in the average meeting by 42 percent between the two steady states in our calibrated model. We refer to this shock as the "policy change" to emphasize its policy-malleability.

Our quantitative answer depends in large part on choosing the meeting and learning parameters that underlie the diffusion process. If we set aside the experimental moments we use to estimate them (discussed more below) and instead set them arbitrarily, the model can deliver anywhere between a 0 and 40-fold increase in average income. Thus, the model does not *ex ante* guarantee small or large gains, but depends on parameter choices. Conceptually, the model delivers large gains when two complementary forces operate in the baseline economy: it must be hard to meet good matches, but agents must be able to learn a lot once they do. The former guarantees the policy change is a large shock. The latter guarantees that shock translates into profitable knowledge that increases the economy's stock of knowledge. If either of those fail to hold, the impact will be smaller. This complementarity, and how various empirical moments relate to it, is central to most of the quantitative results discussed in this paper.

A benefit of the structural model is that we can link these parameters directly to moments from the RCT. We devise a simple estimation strategy that clarifies the relationship between reduced-form moments and the model parameters governing meeting and learning. We show that the average treatment effect (ATE) from the RCT generates a "meeting-learning frontier" that pins down the relative importance of meeting and learning, but not their exact values. An additional moment related to treatment effect heterogeneity separates them. Intuitively, this second step amounts to comparing two otherwise-identical treated firms who are randomly paired with different matches and ask how their *ex post* profit differs. Econometrically, it requires measuring the covariance between a treated firm's *ex post* profit and her match's *ex ante* profit, adjusted by the amount of variation fed into the experiment exogenously. Thus, we use the ATE to compute a set of possible meeting/learning combinations, then measure covariance to choose a specific point among those combinations.

With the estimated learning and meeting technologies, and a relatively standard calibration for the remaining model structure, we find that average income increases by 11 percent in the new steady state. Sixty percent of that effect comes directly from making it easier to meet high-knowledge firms. Because everyone can more easily accumulate knowledge, the equilibrium stock of knowledge increases and thus increases average income. The remaining 40 percent comes from an amplification effect through price changes. More profitable firms demand more workers and therefore pay higher wages. This competitive pressure pushes marginal firms out of business and de-congests learning for everyone else, further expanding the stock of knowledge.

These results show that the model parameters estimated with experimental moments play an important role in governing aggregate outcomes. In addition to quantifying the gains from better matching, we solve the social planner's problem in the Appendix and show that these same parameters play a central role when designing and quantifying the gains from optimal policy. Motivated by this, we use the remainder of the paper to study the relationship between reduced-form moments and aggregate outcomes. We ask when, if ever, it makes sense to extrapolate aggregate implications from the average treatment effect and what additional moments, like the covariance moment used here, add useful information. We do so because the promising results from these interventions – as measured by the average treatment effect – have been used to motivate scaled policy (e.g. World Bank, 2020).

Answering this question requires understanding the marginal discipline provided by each of the experimental moments we use. That is, in the 0-to-4,000 percent range of aggregate income changes the model can deliver, we first ask what subset is consistent with the average treatment (ATE). We find that the shape of the meeting-learning frontier imposed by the ATE rules out exactly the parameter combinations required to generate the largest possible aggregate gains. Specifically, the meeting-learning frontier restricts diffusion parameters to those in which easier meeting is associated with easier learning. The largest aggregate gains – reached when meeting is difficult but learning is easy – require the opposite.

Yet even conditional on the ATE, the model still allows for the possibility of aggregate gains between 5 and 40 percent. The marginal contribution of measuring covariance is to pin down our baseline outcome of 11 percent within this range. Thus, this moment offers quantitatively relevant information about at-scale implications beyond the ATE. Is this always the case? Using the model, we show it does so only when the ATE is large. The rationale again follows from the complementarity between meeting and learning. A small ATE requires either that the baseline economy is characterized by one of two features: either learning is impossible or everyone can already meet high-knowledge matches. Because of the complementarity between the two forces, either implies no scope for aggregate gains. The quantitative variation can be large. While a 1 percent ATE is consistent with aggregate gains between 0.005 and 0.1 percent, a 100 percent ATE is consistent with gains between 10 and 283 percent. Our covariance moment can be estimated with a simple linear regression in experimental data, thus helping to clarify aggregate potential.

Our results show that understanding the link from empirical moments to model parameters has important macro and micro implications. We derive them in a specific model with a specific RCT. But there are many models of diffusion and a growing set of RCTs that have a similar flavor to the one used here (i.e., random opportunities to meet others) but differ in their exact implementation.[2] Our last exercise is therefore to take a step back and ask if there are any more general lessons to be

[2]For example, while our experiment and Lafortune et al. (2018) use one-to-one meetings, Cai and Szeidl (2018) introduce group meetings of firm managers and Atkin et al. (2017) vary buyer-supplier links.

drawn about measurement in partial equilibrium RCTs in the presence of diffusion. We provide sufficient conditions on both the equilibrium diffusion model and RCT used that guarantee the same moments estimate the same model parameters. At the heart of this result is the fact that randomization offers a powerful tool for parameter estimation. By leveraging the same orthogonality conditions used for measuring causal treatment effects, one has to specify only the diffusion "block" of the model for estimation, leaving the remaining model structure to be adjusted to the specifics of the economic setting.

Therefore, while this paper join a recent literature that disciplines macro-development models with experiments to simulate scaled policy (e.g. Buera et al., 2021; Caunedo and Kala, 2022; Fried and Lagakos, 2022; Fujimoto et al., 2023; Kaboski et al., 2022; Lagakos et al., 2022), we further show how to measure additional moments within the RCT that provide relevant information about the gains at scale that are useful for policy decisions.[3] We further link together a growing micro-development literature with a parallel one in macro-development and growth, where the non-rivalrous nature of information or knowledge has long been seen a contributor to aggregate growth (Romer, 1990; Jones, 1995; Kortum, 1997). Jovanovic and Rob (1989), Lucas (2009), Lucas and Moll (2014), and Perla and Tonetti (2014) micro-found the equilibrium diffusion of knowledge between agents, and form the basis for the model we use here.[4] Related to our focus on the complementarity between meeting and learning, Van Patten (2020) and Jones (2022) highlight the importance of different knowledge production functions on various macroeconomic outcomes.

2 Empirical Evidence on the Benefits of Meetings

Recently, several microeconomic studies have documented the potential benefits for firm owners or managers who are randomly chosen to interact with highly skilled individuals. These take the shape of other managers or potentially by interacting through supply chains. We focus on one of those here and take up others in the Appendix. We utilize the randomized controlled trial in Brooks et al. (2018).[5] Space constraints naturally require us leave out some details, but we refer interested readers to Brooks et al. (2018) for other (less critical) details.

[3] An alternative would be to run larger and larger clustered experiments to measure equilibrium effects. In addition to costs, defining catchment areas for clusters is difficult. Muralidharan and Niehaus (2017) discuss the difficulty of defining spillover borders. Berguist et al. (2019) formalize a related issue when attempting to interpret agricultural interventions in the presence of trade flows.

[4] These models have been extended to international trade (Buera and Oberfield, 2020; Perla et al., 2021), innovation policy (Benhabib et al., 2021; Lashkari, 2020), and various types of learning among co-workers (Herkenhoff et al., 2018; Jarosch et al., 2021; Wallskog, 2023).

[5] We use this experiment because we have access to the relevant data, not because we view this particular experiment as better or worse than other similar experiments that fall under our assumptions.

2.1 Details of RCT and Data Collection

The experiment took place in Dandora, Kenya, a dense informal settlement on the outskirts of Nairobi. Via a representative sample of firm owners in Dandora, we randomly matched more profitable entrepreneurs with less profitable ones. We followed the owners over 17 months to measure changes in business practices and profitability over time.

The sample we draw from is the set of female business owners who have been in operation for less than 5 years.[6] We then randomly select a subset of these business owners to randomly match with a more profitable owner. A control group receives no such offer. Firms were then surveyed over 6 quarters to track the time series of treatment.

The set of more profitable owners were selected from those businesses with owners over 40 years old and at least 5 years of experience. This was to minimize the importance of "luck" in baseline profit realizations to allow us to focus on truly productive business owners. We then recruited business owners with the highest profit until we had a sufficient number for matches. Of those contacted, 95 percent accepted. Matches with the treatment firms were randomly created conditional on industry. Figure 6 in Appendix A shows the profit distributions for the full population, the sample of control and treatment firms, and the intervention-defined matches. As expected, our study population is somewhat poorer the average and the matches are drawn from the far right tail.

Anticipating the model and quantitative results, key for our identification is the two layers of randomization. The first is the usual randomization between control and treatment and the second is the randomization of individual matches within the treatment group. It will also be useful going forward to define some relevant distributions. We denote the cumulative distribution of baseline profit for treatment and control firms as $H_{T,\pi}(\pi)$ and $H_{C,\pi}(\pi)$ (which in theory are the same due to randomization). The exogenously-defined matches for the treatment group are distributed with c.d.f. $\widehat{H}_{T,\pi}(\hat{\pi})$.

Details of a "Match" Like any RCT, our matches were designed to remain faithful as possible to the model without sacrificing the practicality required to generate take-up. This necessarily involves trade-offs, which we discuss here. The program was pitched to both sides of the match as a mentee-mentor relationship, and thus was explicitly focused on business success. The more successful business owners were

[6] The sex selection criteria is to limit heterogeneity outside the model. Note, however, that females make up 65 percent of business owners in Dandora and 71 percent of owners with businesses open less than 5 years.

the "mentors," while the less successful were the "mentees." The mentors were told they could potentially help other business owners learn the requisite skills required to operate in Nairobi. We provided no topics to discuss, preferring that the content was self-directed. We offered mentors only some optional, vague prompts in an initial orientation meeting that could be used ("What challenges did your mentee face this week?"). Matches were designed to last for one month, though of course there was no restriction on meeting after the formal end of the program.

One potential concern is our meetings may not necessarily reflect those that underlie the usual matching process, perhaps related to indirectly priming mentees to believe the matches would be beneficial. There is little we can do to rule this out completely.[7] It is a problem common to most randomized controlled trials when attempting any extrapolation outside the study sample. We designed the details to be as light-touch as possible while offering a reasonable chance at successful take-up (i.e., to initiate matches, we simply gave the mentee the phone number of the mentor).

Results are balanced given the randomization and we provide details in Appendix A.

2.2 Treatment Effects and Underlying Mechanisms

Figure 1 begins by plotting the average treatment effect (as a percentage) over time, along with the 95 percent confidence interval. There is a large treatment effect in the immediate aftermath of the treatment period that fades quickly. We test whether our model rationalizes this pattern after laying out the model below, and find that it does.

Mechanisms The observed changes in profit primarily come from lowering input costs, with unit inventory costs falling by 49 percent relative to the control group. Consistent with the cost channel, we find that treated firms are 19 percent more likely to switch suppliers in the aftermath of the treatment. We will take seriously this channel in the next section.

How does this result square with the quick fade-out observed in Figure 1? We find that the economic environment is characterized by substantial buyer-supplier turnover. Sixty-two percent of control firms switch suppliers in the 3 quarters immediately following treatment. Thus, any value procured by firms on this dimension by meeting with others is likely to have a short half-life. As we will show shortly, our

[7] We note, however, that evidence of the mentor's business success are easily visible to the mentee. Mentors had substantially more physical capital and workers, and had a fixed, relatively large buildings from which they conducted business. Moreover, the first meeting took place at the mentor's business. Thus, that the mentor was "good" at running a business would likely have been understood with or without us.

Figure 1: Time Series of the Average Treatment Effect (from Brooks et al., 2018)

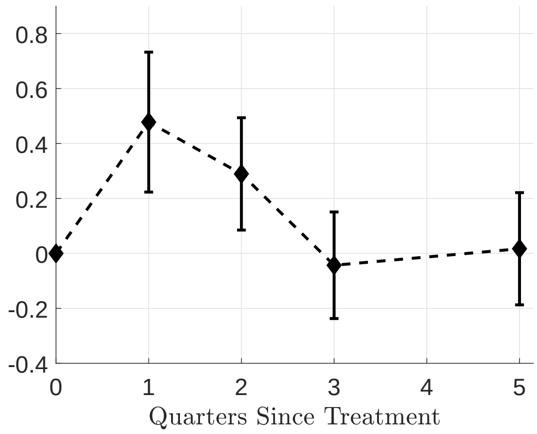


Figure notes: Figure plots average treatment effect as percentage above control mean (0.4 = 40%), along with the 95 percent confidence interval. Treatment takes place between quarters 0 and 1.

model estimation will imply this as well.

Finally, we note that the matches create surplus and are not transfers between the two members in the match. We use the details of the matching procedure to estimate no changes in profitability, scale, or any management practices for the more productive member of the match.[8]

3 A General Equilibrium Model of Diffusion

We now build a full general equilibrium model to study what we learn about the potential aggregate gains from this RCT. We build the model to remain consistent with the economic environment of the study and with the mechanisms highlighted in the previous section. Since the economy is primarily made up of relatively small firms, there is a non-trivial occupational choice decision between wage work and firm operation. We also model a search and bargaining process between firms and suppliers, motivated by the empirical results. Finally, we model a small open economy. Suppliers have access to infinite supply of inputs, consistent with their connection to the broader Nairobi and Kenyan economy. The labor market and diffusion of knowledge are local.

[8]See Brooks et al. (2018) for details on the procedure. This forms the basis for our assumption of the max operator in the model we use below. We also observe no loans, joint input purchases or bulk discounts, profit sharing, or other mechanisms that suggest alternative theories.

3.1 Economic Environment

Time is discrete and infinite. A period is one quarter. There is a unit mass of agents. The state of an agent is her ability to find a supplier z, which evolves over time, and her occupation. We refer to z as an agent's *knowledge* for simplicity. The aggregate state of the economy is the distribution of knowledge, $M(z)$. Each agent dies with exogenous probability δ and a mass δ of new agents replace them each period. New agents draw their initial knowledge from a fixed distribution with c.d.f. $G(z)$.

Every agent has flow utility $u(c, s) = \omega \log(c) + (1 - \omega) \log(1 - s)$, where c is consumption and s is effort (discussed below). ω is the relative weight of consumption in utility. There are no borrowing and savings markets, so consumption is equal to income.

Each period, an agent can choose between running a firm and working at one. Wage work earns the market-clearing wage w, as labor is traded on a competitive market. Firms earn profit $\pi = x^\alpha n^\eta - p_x x - wn$, where x and n are intermediate inputs and labor services, and p_x and w are their respective prices.

Supplier Matching, Input Choice, and the Importance of Knowledge Intermediate purchases require a firm to seek out a supplier. There are a continuum of suppliers indexed by their marginal cost m who earn profit $\pi^s(m, x) = (p_x - m)x$. Suppliers can source from some outside entity and thus can provide whatever amount of input x is requested by firms at marginal cost m. This is consistent with their connection to the broader Nairobi and Kenyan economy.

Firms exert search effort s to find a supplier. Given effort s and knowledge z, the firm matches with a supplier $m = e^{-s} z^{\frac{\alpha+\eta-1}{\alpha}}$. Thus, knowledge here is defined by its ability to lower the effort required to find low-cost suppliers.[9]

Once they meet, the two parties Nash bargain over the price p_x that the firm will pay, taking into account the optimal input choice by the firm at that price. This implies an equilibrium price

$$p_x^*(m) = \text{argmax}_{p_x} \quad (\pi)^\nu (\pi^s)^{1-\nu} \tag{3.1}$$

for bargaining weight ν and the participation constraint that both the supplier and firm earn weakly positive profit.

Knowledge Transmission Knowledge is transmitted between agents. We next discuss the diffusion block of the model that governs this process. First, there is the learning

[9] The constant returns assumption for suppliers eliminates any strategic interactions between supplier-firm bargaining games.

technology that translates meetings into future knowledge. If an agent with knowledge z today meets another agent with knowledge $\hat{z}$, her individual stock of knowledge evolves as

$$z' = e^{c+\varepsilon} z^{\rho} \max\left\{1, \frac{\hat{z}}{z}\right\}^{\beta} \tag{3.2}$$

where c is a constant and ε is an exogenous shock drawn from a distribution with cdf F. The parameter ρ controls the depreciation of knowledge. The final term is the additional benefit meeting another agent. $\beta = 0$ eliminates knowledge transmission. At its other extreme, $\rho = \beta = 1$ simplifies to $z' = e^{c+\varepsilon} \max\{z, \hat{z}\}$.[10]

The second aspect of diffusion is the meeting technology. We assume agents meet operating firms. Denoting M^f as the equilibrium distribution of operating firms (defined formally below), we write $\widehat{M}(\hat{z}; M) = M^f(\hat{z}; M)^{1/(1-\theta)}$. The parameter $\theta \in (-\infty, 1)$ governs how different $\widehat{M}$ is from the existing knowledge distribution of firms, M^f. If $\theta = 0$, then each draw is a random draw from M^f. On the other hand, as $\theta \to 1$, draws become more concentrated in the right tail of M^f. The opposite holds for $\theta < 0$. We refer to θ as the meeting parameter below, since it governs the extensive margin of diffusion.

Occupational Choice Decision and the Knowledge of Firms The aggregate state of the economy is the distribution of knowledge, $M(z)$. At the start of each period, each agent chooses to either operate a firm or engage in wage work given her knowledge z and aggregate state M.

The flow utility of operating a firm is

$$\begin{aligned} u^f(z, M) \quad &= \quad \max_{s,x,n \geq 0} \ \omega \log(x^{\alpha} n^{\eta} - p_x x - wn) + (1-\omega)\log(1-s) \\ s.t. \quad & \quad m = f(s, z) \\ & \quad p_x = \operatorname{argmax}_{p_x} \ \ [\pi]^{\nu} [\pi^s(m)]^{1-\nu} \end{aligned}$$

The first constraint is the type of supplier met with search effort s. The second guarantees that the realized cost is the outcome of Nash bargaining between the firm and its supplier. Flow utility for a worker is $u^w(z, M) = \omega \log(w(z, M))$, where w is the equilibrium wage. We summarize the occupational choice decision as $u(z, M) = \max\{u^f(z, M), u^w(z, M)\}$. We denote decision rule $\phi(z, M) = 1$ as firm operation and $\phi(z, M) = 0$ as wage work.

[10] The max operator in the diffusion process rules out any benefit to the higher knowledge agent in the match. We show later that this is not a critical assumption but does have some empirical support (Brooks et al., 2018; Jarosch et al., 2021). We impose it here because our empirics would require it anyway.

The underlying meeting technology is therefore

$$\widehat{M}(\hat{z}; M) = \left(\frac{\int_0^{\hat{z}} \phi(z, M) dM(z)}{\int_0^{\infty} \phi(z, M) dM(z)} \right)^{\frac{1}{1-\theta}}.$$

Recursive Formulation Taken together, the value of entering the period with knowledge z and aggregate state M is

$$\begin{aligned} v(z, M) &= \max\{u^f(z, M), u^w(z, M)\} + (1-\delta) \int_{\varepsilon} \int_{\hat{z}} v(z'(\hat{z}, \varepsilon; z), M') \widehat{M}(d\hat{z}, M) dF(\varepsilon) \\ s.t. \quad & z'(\hat{z}, \varepsilon; z) = e^{c+\varepsilon} z^{\rho} \max\left\{1, \frac{\hat{z}}{z}\right\}^{\beta} \end{aligned}$$

Equilibrium We study the stationary equilibrium of this model, which includes the value function v, decision rules for occupation $\phi(z, M)$, effort $s(z, M)$, labor $n(z, M)$, and intermediates $x(z, M)$, bargaining outcomes $p_x(z, M)$, and a knowledge distribution $M(z)$, such that the value functions solve the agent's problem above with the associated decision rules, and the aggregate state evolves according to

$$\begin{aligned} & M'(z') := \Lambda(M(z')) \\ = \; & \delta G(z') + (1-\delta) \int_0^{\infty} \int_0^{\infty} F(\log(z') - \rho \log(z) - \beta \log(\max\{1, \hat{z}/z\}) - c) \widehat{M}(d\hat{z}; M) M(dz). \end{aligned}$$

$\Lambda(M)$ is the law of motion for the aggregate state. It consists of the knowledge of new entrants, $\delta G(z)$, and the evolution of knowledge for surviving agents. In the stationary equilibrium, $M^*(z) = \Lambda(M^*(z))$.

3.2 Characterization of Equilibrium

We summarize a few useful features of the equilibrium in the following proposition, with the proof in the Appendix.

Proposition 1. *The following results hold in the equilibrium of the model:*

1. *The solution to the Nash bargaining game is a constant markup over marginal cost, $p_x(m) \propto m$.*

2. *The equilibrium profit function can be written as $\pi(z, w) = A(w)z$, where $A(\cdot)$ depends only on the equilibrium wage and parameters of the model.*

3. *All agents with $z \geq \underline{z}$ operate firms. That cut-off is given by the function $\underline{z}(w) = w^{\frac{1-\alpha}{1-\eta-\alpha}} C$ for a constant C.*

The first two results of Proposition 1 turn out to be useful for calibration below.[11] The occupational choice margin is creates an externality in the model. Since agents do not take into account how their occupational choice affects the learning of others, the decentralized economy allocates more agents to firm operation than the planner would (we solve the planner's problem in Appendix D). We isolate the importance of this margin in the quantitative results below.

3.3 Model Calibration

We now turn to calibrating the model. This involves two steps. In the first step we estimate the diffusion parameters that govern learning (β, ρ) and meeting (θ). We show how these parameters are determined by moments from the RCT, formalizing the relationship between the reduced form moments and the model. A useful feature of the partial equilibrium RCT is that we can estimate these parameters independent of the remaining model structure. We can fix them during the second step, which is a more standard calibration. The ability to separate the diffusion parameter estimation from the remaining calibration plays a larger role when we generalize this procedure in Section 5. The full set of moments and parameter values are reported in Table 2.

3.3.1 The Link from RCT Moments to Diffusion Parameters

When we estimate the diffusion parameters we restrict attention to the baseline and survey wave 1 quarter post-treatment. We first discuss the relationship between the average treatment effect and model parameters, which defines what we refer to as the meeting-learning frontier. We then show how an additional moment, related to covariance within the treatment, allows us to separate meeting (θ) and learning (β, ρ) parameters.

The Meeting-Learning Frontier and the Average Treatment Effect Define the observed average treatment effect from the RCT as ATE^{data}. Measured in percentage terms, $ATE^{data} := \mathbb{E}[\pi'_T]/\mathbb{E}[\pi'_C]$. After imposing the results of Proposition 1 and some additional algebra, the model's counterpart is

$$ATE^{model} = \frac{\int\int \pi^{\rho} \max\{1, \hat{\pi}/\pi\}^{\beta} \, d\widehat{H}_{T,\pi}(\hat{\pi}) dH_{T,\pi}(\pi)}{\int\int \pi^{\rho} \max\{1, \hat{\pi}/\pi\}^{\beta} \, dM^{f}_{\pi}(\hat{\pi})^{1/(1-\theta)} dH_{C,\pi}(\pi)} \tag{3.3}$$

[11] That $\pi(z, w) = A(w)z$ follows because matching between suppliers and firms is deterministic. Uncertainty these matches is straightforward to include. It requires an adjustment to the diffusion parameter estimation analogous to a measurement error adjustment. We discuss this measurement error extension in the Appendix.

where $H_{T,\pi}$, $H_{C,\pi}$ are the empirical c.d.f.s of baseline profit for treated and control firms and $\widehat{H}_{T,\pi}$ is the empirical c.d.f. of the matches for treated firms.[12] ATE^{model} is the average treatment effect that would result from running the same RCT from Section 2, but interpreted through the lens of our model with parameters (β, ρ, θ).

Deriving (3.3) relies on two features. First, it relies on randomization between control and treatment. This allows us to eliminate unobserved shocks ε from both numerator and denominator. Second, it relies on Proposition 1, which allows us to translate unobservable knowledge into observable profit. This leaves only learning parameters (β, ρ) and meeting parameter θ as unknowns. We show how the ATE disciplines model the relationship between these parameters in Proposition 2.

Proposition 2. *For any given values (β, ρ) there is at most one θ such that $ATE^{model} = ATE^{data}$. If $ATE^{data} \in [\Gamma^{min}, \Gamma^{max}]$ that θ exists and is unique. If $ATE^{data} \notin [\Gamma^{min}, \Gamma^{max}]$ then no such θ exists. The bounds are given by*

$$\begin{aligned}
\Gamma^{min} &= \inf_{\theta} \frac{\int\int \pi^{\rho} \max\{1, \hat{\pi}/\pi\}^{\beta} \, d\widehat{H}_{T,\pi}(\hat{\pi}) dH_{T,\pi}(\pi)}{\int\int \pi^{\rho} \max\{1, \hat{\pi}/\pi\}^{\beta} \, dM_{\pi}^{f}(\hat{\pi})^{1/(1-\theta)} dH_{C,\pi}(\pi)} \\
\Gamma^{max} &= \sup_{\theta} \frac{\int\int \pi^{\rho} \max\{1, \hat{\pi}/\pi\}^{\beta} \, d\widehat{H}_{T,\pi}(\hat{\pi}) dH_{T,\pi}(\pi)}{\int\int \pi^{\rho} \max\{1, \hat{\pi}/\pi\}^{\beta} \, dM_{\pi}^{f}(\hat{\pi})^{1/(1-\theta)} dH_{C,\pi}(\pi)}.
\end{aligned}$$

Proposition 2 shows that for any value of the learning parameters (β, ρ), there is a corresponding meeting parameter θ that rationalizes the ATE, up to the bounds Γ^{min} and Γ^{max}.[13] We refer to this function $\theta(\beta, \rho)$ that is consistent with ATE^{data} as the *meeting-learning frontier*. We add an empirically-relevant corollary in Corollary 1.

Corollary 1. *If treatment matches $\widehat{H}_{\pi}(\hat{\pi})$ first order stochastically dominate control matches $M_{\pi}^{f}(\hat{\pi})^{1/(1-\theta)}$ (that is, the intervention offers better matches than agents usually receive) then $\partial\theta/\partial\beta > 0$ on the set for which θ is defined.*

Corollary 1 says that the meeting-learning frontier restricts to parameter combinations in which the ease of learning and meeting positively co-move. While the proof follows closely from the FOSD assumption, the economic intuition follows from model's ability to trade off learning versus meeting when matching ATE^{data}. Because easier learning (higher β) increases the average value of the treatment, ATE^{model}, the model infers it must be easy for agents to find high-knowledge matches without the intervention (higher θ). This lowers the value of the intervention: if agents can already

[12] In principal, with perfect randomization, we could assume $H_{T,\pi} = H_{C,\pi}$. This is irrelevant for our purposes as long as the profit distributions are observable.

[13] These bounds guarantee the treatment effect can be rationalized by the model. For example, if $\beta = 0$, learning is impossible and the model therefore cannot rationalize any non-zero treatment effect. Correspondingly, $\beta = 0$ implies $\Gamma^{min} = \Gamma^{max} = 0$. Usefully, these bounds are computable with the relevant RCT data and estimates (β, ρ).

find high-knowledge agents, the value of offering them one exogenously is of little value. This restriction will play an important role in understanding the quantitative discipline offered by the ATE.

More immediately, however, the results show that we first require estimates of (β, ρ) before we can estimate θ. We turn to that next.

Estimating (β, ρ) from Treatment Data The learning parameters β and ρ are defined in equation (3.2).[14] These control the change in knowledge conditional on receiving a match $\hat{z}$. To estimate these parameters, we first re-write the law of motion in terms of profit because $z \propto \pi$ in equilibrium (Proposition 1), yielding

$$\log(\pi') = \tilde{c} + \rho \log(\pi) + \beta \log\left(\max\left\{1, \frac{\hat{\pi}}{\pi}\right\}\right) + \varepsilon \tag{3.4}$$

where π and $\hat{\pi}$ represent an individual and her match's profit, and $\tilde{c}$ is a constant.

If we consider just treated firms (and denote that set $\mathbf{T}$) and note that in our RCT $\hat{\pi}_i \geq \pi_i \quad \forall i \in \mathbf{T}$, we can drop the max operator and are left with

$$\log(\pi_i') = \tilde{c} + \rho \log(\pi_i) + \beta \log\left(\frac{\hat{\pi}_i}{\pi_i}\right) + \varepsilon_i \qquad \text{for } i \in \mathbf{T}. \tag{3.5}$$

Equation (3.5) is a linear regression run only on treated firms, regressing *ex post* profit on *ex ante* own and match profit. These estimated coefficients $(\hat{\beta}, \hat{\rho})$ are equal to their structural counterparts. Because all treatment matches are randomized, within-treatment comparisons are unbiased. Therefore, the result does not depend on the ε shocks being i.i.d.. A second benefit of leveraging within-treatment randomization is that θ does not enter into the estimating equation. When combined with Proposition 2, we then have estimates of all three parameters.

For some intuition on the relationship between the model parameters and empirical moments, note that the estimate $\hat{\beta}$ can be written as

$$\hat{\beta} = \frac{cov(\log(\pi_i'), \log(\hat{\pi}_i))}{\sigma^2_{\log(\hat{\pi})}}.$$

β therefore measures the covariance between a firm's *ex post* profit and its match's *ex ante* profit, normalized by the amount of exogenous variation fed into the experiment. This exogenous variation is measured by the log profit variance of the exogenous intervention-defined matches $\sigma^2_{\log(\hat{\pi})}$. Somewhat more intuitively, it tells us how match quality changes a firm's knowledge. If two treated firms meet with firm owners of

[14] For ease of reference, recall that (3.2) is $z' = e^{c+\varepsilon} z^{\rho} \max\left\{1, \frac{\hat{z}}{z}\right\}^{\beta}$.

different profitability but have similar *ex post* profit, the model infers that $\beta = 0$, or that no learning can occur.

Diffusion Parameter Estimates The preceding discussion implies a straightforward estimation strategy. First, we run regression (3.5) on all treated firms and get estimates $(\hat{\beta}, \hat{\rho})$. We then estimate $\hat{\theta}$ so that the model ATE matches the observed ATE^{data}.[15]

The results of the first step are in Column (1) of Table 1, and we find that $\beta = 0.538$ and $\rho = 0.595$. ρ measures the persistence of profit after properly controlling for different matches between treated firm owners. We find that profit is not very persistent, at least relative to measures in richer countries or among larger firms. This is consistent with the mechanisms discussed in the previous section. The result $\hat{\beta} = 0.538$ implies there is a strong, but far from perfect, internalization of match knowledge. The second step is in Column (2) of Table 1. This implies $\theta = -0.417$. For a sense of magnitude, this implies that the expected match knowledge is 95 percent of the knowledge of the average operating firm. Matches are slightly worse than uniformly random draws from the operating firm distribution.

Table 1: Moments for Diffusion Parameter Estimation

	(1)	(2)
β	0.538	
	(0.273)**	
ρ	0.595	
	(0.273)**	
Treatment		891.990
		(280.720)***
R^2	0.053	0.047
Control Avg	–	1897.851

Table notes: Standard errors are in parentheses. The top and bottom one percent of dependent variables are trimmed. Statistical significance at 0.10, 0.05, and 0.01 is denoted by *, **, and, ***.

3.3.2 Calibration of Remaining Parameters

We next calibrate the remaining parameters, holding fixed our previously estimated diffusion parameters. We make use of the baseline field data that is a representative sample of firms in Dandora, Kenya to calibrate to the local economy.

We assume both exogenous shock processes are lognormal, so that new entrants draw from $G \sim logN(\mu_0, \sigma_0)$ and existing firms from $F \sim logN(\mu, \sigma)$. We normalize $\mu_0 = 0$. We note that the drift in the learning function c and the mean of the

[15] This requires checking that ATE^{data} falls within the bounds of Proposition 2 at estimates $(\hat{\beta}, \hat{\rho})$, which it does.

exogenous shocks for existing firms, μ (from c.d.f. F), are not separately identified. We set $\mu = -\sigma^2/2$ so that $\mathbb{E}[e^{\varepsilon}] = 1$. This leaves 8 remaining parameters. On the utility side, they include the relative weight of consumption ω and the agent death rate δ. The remaining parameters dealing with technology and knowledge evolution are the parameters α and η, the knowledge growth term c, and the standard deviations of the exogenous shocks σ_0 and σ. The final parameter is the bargaining weight ν.

These remaining 8 parameters can be broken into two groups. The first group is matched one-to-one with a given moment or value (δ, σ_0, ν). The death rate δ is set average age of population in the study, which is 34.[16] The standard deviation of new entrant knowledge matches the variance of log profit for firms that have been open for less than 3 months, which implies $\sigma_0 = 1.00$. Finally, we note that given the model set-up the bargaining power of firms in its supplier negotiation (ν) has no effect the results. Thus, we set it as $\nu = 0.5$ for simplicity.

This leaves 5 parameters – σ, c, ω, α, and η – which we target to jointly hit 5 moments. While jointly calibrated, each has an intuitive counterpart. We choose σ to match the standard deviation of log profit in the economy, equal to 0.99. The drift parameter c is targeted to match the average profit of all firms relative to those who entered less than one year ago (1.51). The utility parameter ω is set to match the share of employment in wage work. The most recent Kenyan census (via IPUMS, 2020) implies that 48 percent of employment in Embakasi Constituency (the local area in Kenya that includes our study site) is in wage work.

α and η are then set to match two moments. The first moment is the wage bill relative to intermediate spending. The average firm has a relative wage bill of 0.13. Our Cobb-Douglas assumption implies that $wn/p_x x = \eta/\alpha$, so we can set $\eta = 0.13\alpha$. Next, a consequence of Proposition 1 is that

$$\sigma_{\log(p_x)} = \left(\frac{1-\alpha-\eta}{\alpha}\right)\sigma_{\log(\pi)}. \tag{3.6}$$

The left-hand side is the standard deviation of log unit intermediate costs across firms. We find that $\sigma_{\log(p_x)} = 1.61$ in our baseline data after removing industry fixed effects. Since $\sigma_{\log(\pi)} = 0.99$ is also matched in the calibration, rearranging (3.6) after imposing these empirical estimates and $\eta = 0.13\alpha$ implies

$$\alpha = \frac{\sigma_{\log(\pi)}}{\sigma_{\log(p_x)} + 1.13\sigma_{\log(\pi)}} = \frac{0.99}{1.61 + 1.13 \times 0.99} = 0.36$$

The complete list of moments and parameter values are in Table 2.

[16]The constant death rate δ implies a geometrically distributed age distribution with mean $1/\delta$ and, assuming a new agent is 18 years old, implies an average age of 64 quarters in the model. We match actual age rather than age of the firm because agents can move between firm operation and wage work during their lifetime.

Table 2: Targets and Parameter Choices

Model Parameter	Description	Parameter Value	Target Moment	Source	Target Value	Model Value
Group 1	*Diffusion Block from RCT*					
β	Intensity of diffusion	0.538	Estimated parameter from regression (5.5)	RCT results	0.538	0.538
ρ	Persistence of knowledge	0.595	Estimated parameter from regression (5.5)	RCT results	0.595	0.595
θ	Match technology "quality"	-0.417	Treatment effect in quarter 2 (as % above control)	RCT results	0.403	0.403
Group 2	*Matched one-to-one with parameter*					
δ	Death rate of firms	0.016	Average age of baseline business owners	Baseline survey	0.09	0.09
σ_0	St. dev. of new entrant knowledge distribution	1.00	Variance of log profit among new entrants	Baseline survey	1.00	1.00
ν	Firm bargaining weight	0.50	Set exogenously	–	–	–
Group 3	*Jointly targeted*					
σ	St. dev. of exogenous knowledge shock distribution	0.73	Standard deviation of log profit in all firms	Baseline survey	0.99	0.99
c	Growth factor in knowledge evolution	-2.11	Ratio of average profit of all firms to new entrants	Baseline survey	1.51	1.51
ω	Consumption utility weight	0.47	Fraction of employment in wage work	IPUMS	0.48	0.48
α	Knowledge elasticity in supplier search	0.36	Standard deviation of log inventory cost	Baseline survey	1.61	1.61
η	Knowledge elasticity in supplier search	0.05	Average cost ratio	Baseline survey	0.13	0.13

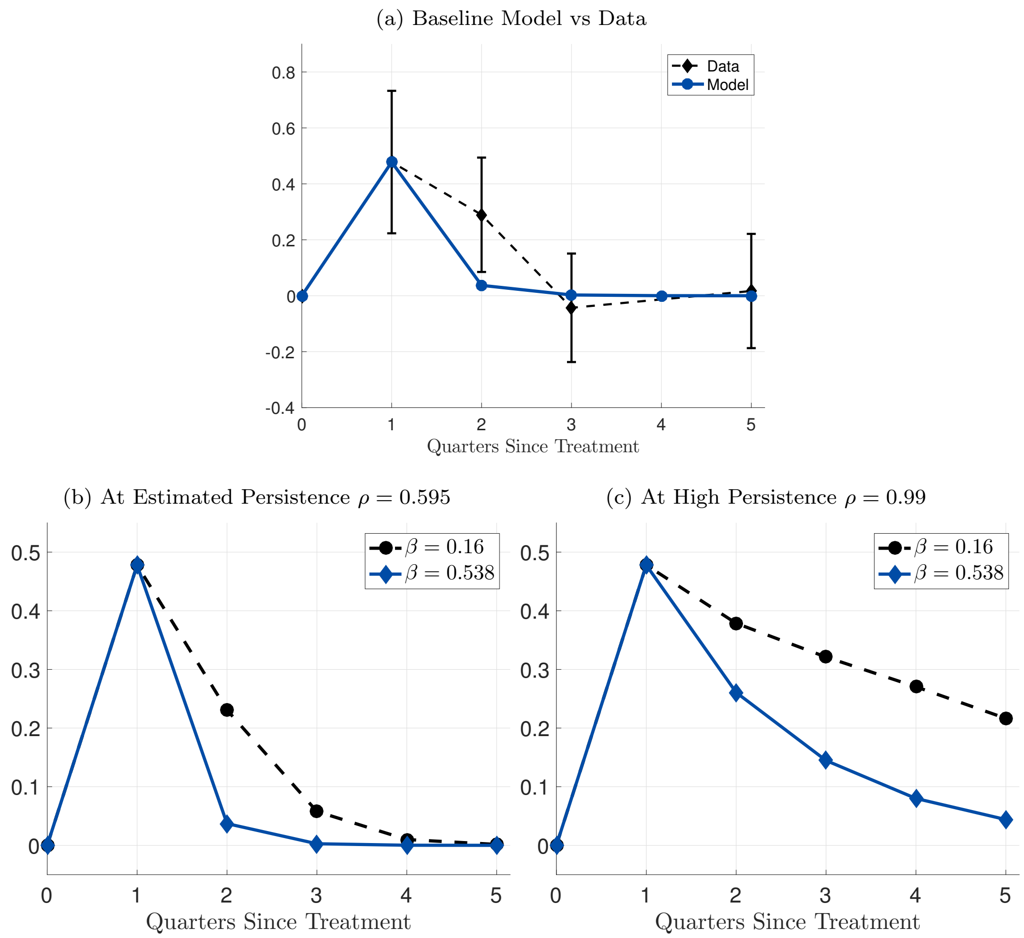
Table notes: Group 1 is jointly chosen from the experimental data. Group 2 are also set to match baseline data moments, but match 1-1 with target moments. Parameters in Group 3 are calibrated to jointly match moments.

3.4 Dynamic Treatment Patterns

Our calibration does not use the full time series of the average treatment effect, only the data before and the first period after treatment. Before turning to the quantitative results we ask if the model can replicate the observed pattern. Figure 2a replicates the time series of the ATE over 5 quarters in the model. The first two quarters are matched by construction. Both the model and data predict no treatment effect by $t = 3$. The model under-predicts the effect in $t = 2$ so, if anything, the model understates the partial equilibrium RCT dynamics.

Figures 2b and 2c show how the learning parameters β and ρ inform our model prediction. If we instead estimated a high knowledge persistence (high ρ) and low ability to learn (low β), we could have instead predicted a 20 percent treatment effect at $t = 5$. Thus, the parameter estimates from the RCT put discipline on the fade-out pattern we predict from the model.

Figure 2: Relationship between Treatment Persistence and Diffusion Intensity β



One interesting result here is that higher β hastens fade-out. As we discuss below in the quantitative results, higher β is also critical for generating general equilibrium gains from diffusion. An immediate consequence of the results here is that treatment effect persistence need not be positively correlated with the equilibrium gains that could be achieved at scale. This difficulty in linking average treatment effect moments to at-scale equilibrium implications is a theme we will revisit in the quantitative results.

4 Quantitative Results

With the calibrated model in hand, we now turn to quantitative results. The goal is to understand the equilibrium implications of better meeting technologies. We implement this by increasing the meeting parameter θ so that it moves 25 percent closer to its limit of $\theta = 1$. This increases baseline $\theta = -0.417$ to $\theta^{new} = -0.063$. We think of this is as an aggregate policy change motivated by the RCT discussed earlier, which offers the same increase in meeting quality.[17] We study the long run, general equilibrium change in income that results by comparing the two stationary equilibria.

4.1 Impact of Better Matches in Equilibrium

Aggregate moments are reported in Table 3. The first column is the baseline economy ($\theta = -0.417$) with aggregate moments from the stationary equilibrium normalized to one. The second column presents a new equilibrium with $\theta^{new} = -0.063$ but fixes the wage at the baseline level. Column three allows the wage to adjust as well.

Overall, income rises by 11 percent. This is made up of two general equilibrium effects. The first is that the new matching technology directly affects the knowledge distribution by making it easier to learn from high-knowledge agents. The second is an amplification effect through prices.

We decompose the relative importance of these two channels in columns 2 and 3. Column 2 isolates the direct effect. Average knowledge rises by 7 percent and the labor supply declines by 10 percent as the distribution shifts mass across the (fixed) cut-off ability level that defines occupational choice (see Proposition 1). Average income rises by 7 percent.

[17]The choice of 25 percent is somewhat arbitrary, but also irrelevant for our results net of some differences in magnitudes. In practice, policy changes are often motivated by experiments but are not exact replications for administrative reasons. We think of this as a policymaker creating a program that has the same spirit as the smaller scale intervention. This could be through extension programs, better use of information technology, or explicit mentoring programs, among others. For some sense of magnitude, this increase in θ increases expected match knowledge by 42 percent in the new steady state. In the Appendix we provide the results when the aggregate policy exactly replicates the estimated RCT gains. The same results hold with larger magnitudes.

Table 3: Equilibrium Moments

	(1) Baseline	(2) Fixed Wage	(3) New Equilibrium
Income	1.00	1.07	1.11
Ability	1.00	1.07	1.12
Aggregate Wage-Labor Supply	1.00	0.90	0.98
Wage	1.00	1.00	1.13

Table notes: Column (1) is the initial equilibrium, normalized to one. (2) and (3) report the new stationary equilibrium after shocking the matching technology, where (2) holds the wage fixed at its baseline level and (3) allows it to adjust.

Column 3 allows the equilibrium wage to adjust. The wage increases by 13 percent as the knowledge required to find lower-cost suppliers increases the marginal product of labor. This competitive pressure causes the lowest knowledge firms to exit and work for a wage instead. Removing relatively low quality firms allows for easier learning. This amplifies the direct effect on ability through the diffusion process.

Of the total increase in knowledge, 61 is from the direct effect and 39 is from the amplification through prices. A similar magnitude holds for income. Both forces play a quantitatively relevant role in generating the aggregate gains.

4.2 Complementarity Between Meeting and Learning

We next turn to understanding how the model generates this 11 percent increase in income, and what factors play a major role. At the heart of our results is understanding the complementarity between meeting and learning. To see this, we start by measuring the quantitative impact of our policy shock (increasing baseline θ to $\theta^{new} = -0.063$) under various combinations of baseline meeting (θ) and learning (β, ρ) parameters. Throughout, we hold the remaining calibration fixed. These results are in Figure 3.

We start by focusing on the set of possible outcomes in the model. This set is shaded in gray in Figure 3. Depending on the parameters chosen, average income rises by anywhere from 0 to more than 4,000 percent. Complementarity between meeting and learning drives this result. All else equal, the gains are larger when it is more difficult at baseline to meet high-knowledge agents. That is, the larger the difference between baseline θ and $\theta^{new} = -0.063$, the larger the change in the meeting technology. But Figure 3a shows that even if θ is low, a wide range of aggregate outcomes remains possible. This is a function of the complementarity. If no one can learn ($\beta \approx 0$), there is no aggregate benefit regardless of θ. But if it

Figure 3: Possible Outcomes for Different Diffusion Parameters

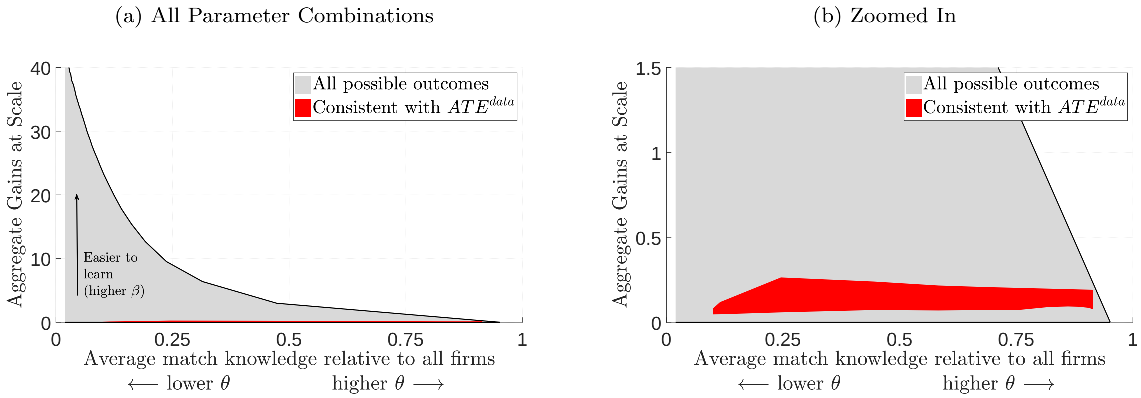


Figure notes: Aggregate income change after shock to $\theta^{new} = -0.063$. We consider the range $\theta \in [-250, -0.063]$ and $(\beta, \rho) \in [0, 0.99] \times [0, 0.99]$. Each economy holds the remaining calibration fixed at baseline parameter values. Figure 3b is a zoomed-in view of Figure 3a around the ATE-consistent outcomes. Multiply the vertical axis by 100 to get percentage gains (i.e., $5 \equiv 500\%$).

easy to learn ($\beta \approx 1$), the aggregate gains can be extreme: over a 40-fold increase in income. The opposite also holds. As meeting becomes easier ($\theta \approx \theta^{new}$), the policy offers less benefit regardless of how easy it is to learn.

To summarize, large economic benefits require two features of the model to simultaneously hold. First, it must be difficult to meet high-knowledge agents before the policy change. Second, it requires that agents can take advantage of that policy change once it occurs. The aggregate gains therefore depend on properly measuring the two technologies that govern this process and may be large or small depending on which way the empirics push these parameters. The average treatment effect measures how large the shock is in literal terms – the distance between the baseline θ and θ^{new}. Covariance within the treatment then measures the scope for translating that shock into profitable knowledge.

4.3 Predicting Aggregate Outcomes with RCT Moments

Two other results emerge from Figure 3. First, the most extreme possible outcomes are inconsistent with the average treatment effect. These ATE-consistent outcomes are overlaid in red and are only a small subset of potential outcomes. Second, that ATE-consistent subset remains large in an absolute sense. The aggregate gains still range from 5 to 40 percent. This implies that our covariance moment plays an important role in predicting aggregate outcomes.

We answer two related questions here that speak to both the mechanics of the model and, relatedly, what those mechanics imply for interpreting reduced form moments. First, we show how the average treatment effect rules out extreme outcomes from the model. Second, we show that our covariance moment adds important information about at-scale implications only when the average effect is large. Both are informed by the same complementarity highlighted above.

4.3.1 Why the ATE rules out extreme outcomes

We first detail the marginal discipline provided by the average treatment effect (ATE). To start, Figure 4a shows the θ required to match the ATE for any set of learning parameters β and ρ. That is, we trace out the meeting-learning frontier discussed in the estimation section (Section 3.3.1). Figure 4a shows the positive relationship between the assumed learning parameters and the implied meeting parameter θ. The higher the assumed (β, ρ), the closer to zero θ must be to match ATE^{data}.[18]

Figure 4: Aggregate Implications of Varying (β, ρ) at Baseline ATE

(a) Implied θ (b) Aggregate Gains

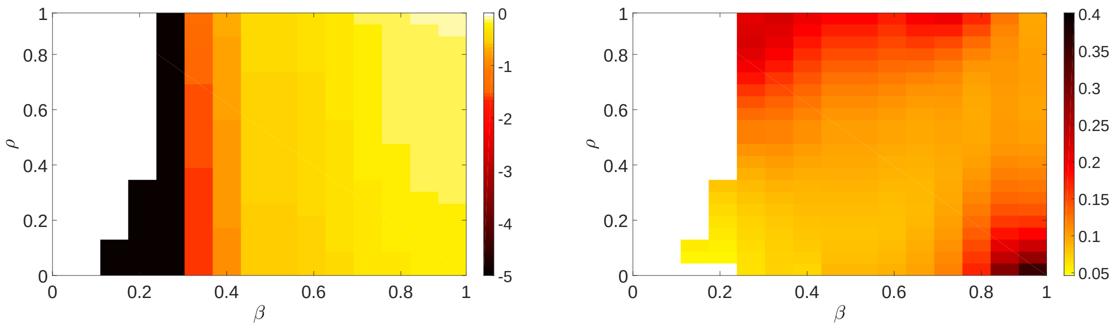


Figure notes: For each value of (β, ρ), (a) plots the implied θ that guarantees the model hits our baseline ATE, ATE^{data}. (b) then plots the implied percentage change in average income from better matching ($\times 100$ for percent, i.e., $0.4 = 40\%$). Dark colors represent larger absolute values and white space means that it is not feasible to match our ATE at the given values of β and ρ.

As discussed in Section 3.3.1, this pattern follows from the way the model can rationalize ATE^{data}. First, it can appeal to learning. The easier learning is (β is high), the larger the benefit from replacing the original meeting technology with a better one. Second, it can appeal to the meeting technology. The worse it is at baseline (lower θ) the larger the impact from replacing it.

These two features must both be true to generate large aggregate gains in the model, which are generated by the complementarity between difficult meeting and easy learning. But the ATE implies that these cannot both hold simultaneously. Otherwise, the ATE implied by the model would be higher than what we observe in

[18]Below $\beta = 0.145$ there are no values of θ that remain consistent with ATE^{data}.

the data. This is the crux of the quantitative discipline offered by the ATE. It creates a meeting-learning frontier to match the observed average treatment effect and, in doing so, eliminates many of the most extreme outcomes the model offers.

Figure 4b then plots the aggregate gains that are consistent with our observed ATE. The largest equilibrium gains (40 percent) are available at high β and low ρ in the bottom right of Figure 4b. The rationale here is that higher β and ρ both lower the implied θ, but β plays a larger role in aggregate outcomes than ρ. Thus, setting $\rho = 0$ and $\beta = 1$ creates the largest θ shock without sacrificing too much of the amplification from learning.

4.3.2 When does covariance offer additional information about at-scale outcomes?

While the ATE eliminates many of the largest possible aggregate income changes, Figure 4b still shows that our ATE is consistent with gains between 5 and 40 percent. This is the benefit of measuring covariance – it pins down the 11 percent income increase within this range.[19] Given the size of this range of possible outcomes, this covariance moment offers quantitatively important information about at-scale outcomes.

In this section, we ask whether this is always true. We find that covariance proves particularly useful to measure when the ATE is large. Or put differently, it is riskiest to extrapolate directly from the ATE specifically when the ATE is large. To see this, we replicate the exercise above, but instead of using our observed ATE^{data}, we assume we instead observe counterfactual ATEs between 0 and 100 percent. For each one, we compute the band of aggregate outcomes that are consistent with it. Those results are in Figure 5.

While a 1 percent ATE admits a fairly narrow band of aggregate gains between 0.01 and 0.05 percent, a 100 percent ATE admits gains between 10 and 285 percent. Thus, while a small ATE accurately predicts a small general equilibrium impact at scale, a large ATE offers a much wider set of possibile at-scale outcomes. The intuition follows almost directly from the same complementarity highlighted above. With an ATE near zero, the model requires that either learning is extremely difficult ($\beta \approx 0$) or everyone can easily meet high-knowledge matches ($\theta \approx \theta^{new}$). Either of these implies no scope for aggregate gains. Thus, extrapolating from the ATE is warranted. On the other hand, a high ATE demands some combination of easier learning (β high) and worse baseline meetings (θ low). This opens scope for potentially large aggregate

[19] Recall that this covariance moment is the estimate β from the regression $\log(\pi_i') = \tilde{c} + \rho \log(\pi_i) + \beta \log\left(\frac{\hat{\pi}_i}{\pi_i}\right) + \varepsilon_i$ run only on treatment firms. This is equation (3.5) in the estimation and is reproduced here as a reminder. We refer to it as covariance because its closed form is $\hat{\beta} = \frac{cov(\log(\pi_i'), \log(\hat{\pi}_i))}{\sigma^2_{\log(\hat{\pi})}}$.

Figure 5: Relationship between average treatment effect and equilibrium increase in income

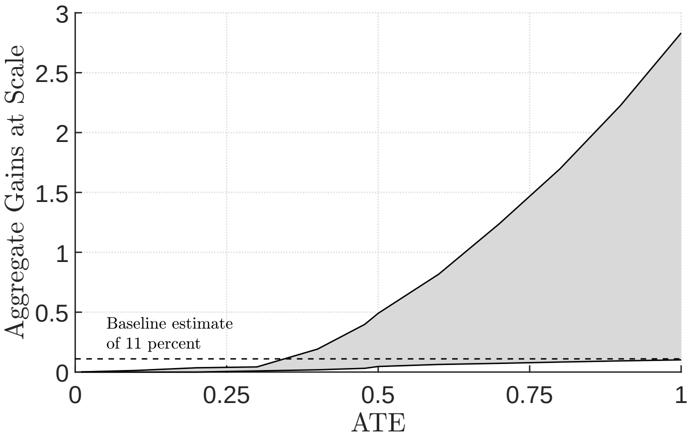


Figure notes: The shaded region shows all possible realizations of aggregate gains that can be achieved while holding the average treatment effect fixed by re-estimating the extensive margin parameter θ for each (β, ρ) combination. Multiply by 100 for percentage gains.

gains which is driven by the complementarity between exactly these two forces. Thus, extrapolating from the ATE is no longer warranted.

To see this slightly differently, Figure 5 shows that our 11 percent ATE is consistent with average treatment effects between 35 percent and 100 percent. In summary, measuring covariance turns out to be particularly important when interpreting evidence from RCTs that create large partial equilibrium benefits for the average participant. Moreover, it can be easily estimated in intervention-level data, making it a relatively straightforward moment to measure. On the other hand, covariance offers little additional information when experimental results show no effect on average.

Finally, and motivated by these results, our last exercise in Section 5 ask the extent to which these same moments estimate the same parameters in a broader class of models and experiments, or whether they rely on specific details of our Kenyan intervention or the model we write down.

5 Broader Lessons for Understanding RCT Gains at Scale

While our previous results focus on one specific RCT to fix ideas, Brooks et al. (2018) is part of a broader set of RCTs that create random meeting opportunities for firm owners. Moreover, the promising results of these RCTs have been used as evidence for large-scale policy decisions (e.g., World Bank, 2020). In this final section, we take a step back to probe whether our results provide any more general guidance on measurement in these types of partial equilibrium RCTs when the economic environment includes the possibility of diffusion.

We ask specifically whether we can use the same moments to pin down the same diffusion parameters in a broader class of models and interventions. To do so, in this section we lay out sufficient conditions that guarantee the same procedure holds. These conditions turn out to cover a wide range of potential models and interventions. We begin by laying out the economic environment, then describe a class of interventions as a data-generating process from the model.

5.1 Class of Models

When we set up both the model and data-generating process to generalize away from the model developed in Section 3, we need to introduce slightly more terminology. The first is the distinction between an individual agent in the model and an imitation opportunity. In Section 3, they are the same. If person i meets with person j, i's imitation opportunity is $\hat{z}_i = z_j$. But these are conceptually separate notions. For example, if i meets with a group of agents $j_1, \ldots, j_N$ and receives the average knowledge of those N agents, i's imitation opportunity would be $\hat{z}_i = (1/N)\sum_{k=1}^{N} z_{j_k}$. Therefore, when we discuss matching below, it is important to keep in mind that these are imitation opportunities, not necessarily individual model agents. With that caveat noted, we turn to defining a class of models.

Time is discrete, and there is a population of agents with knowledge z. We make three assumptions on the economic environment. The first is how knowledge evolves.

Assumption 1. *Given knowledge z this period, an imitation opportunity $\hat{z}$, and a random shock ε, ability next period z' is given by*

$$z'(z, \varepsilon, \hat{z}) = e^{c+\varepsilon} z^{\rho} \max\left\{1, \frac{\hat{z}}{z}\right\}^{\beta}, \tag{5.1}$$

where the parameter c is a constant growth term, β is diffusion intensity, and ρ is persistence. ε is uncorrelated with z and $\hat{z}$ but is not i.i.d. across agents.

This assumption mirrors our technological learning assumption used in the model of Section 3, though we offer generalizations in the Appendix. The next two assumptions are on equilibrium outcomes of the model. The first relates unobservable knowledge z to observable characteristics.

Assumption 2. *In any period, equilibrium profit π is proportional to knowledge. For any two agents i and j, $\pi_i/\pi_j = z_i/z_j$.*

This result holds in our model in equilibrium. The critical feature in Assumption 2 is that there exists some way to move between unobserved knowledge z and observable characteristics. Thus, we can allow more general relationships that include, for example, production function estimation which we consider in the Appendix.[20]

Finally, the third assumption puts characteristics on the source distribution from which imitation opportunities $\hat{z}$ are drawn in equilibrium. We denote the cumulative density function of $\hat{z}$ as $\widehat{M}(\hat{z}; z, \theta)$. $\widehat{M}$ implies that different z agents can draw from different distributions and those distributions depend on a technological parameter θ. The role of θ is summarized in Assumption 3.

Assumption 3. *The source distribution of imitation draws $\hat{z}$ can be characterized in equilibrium by a cumulative density function of the form $\widehat{M}(\hat{z}; z, \theta)$ with the following properties:*

1. *For every z and $\hat{z}$, $\widehat{M}$ is continuous in θ*
2. *$\theta_1 < \theta_2 \implies \widehat{M}(\hat{z}; z, \theta_2)$ first order stochastically dominates $\widehat{M}(\hat{z}; z, \theta_1)$.*

Our assumption in Section 3 that $\widehat{M}(\hat{z}; z, \theta) = M^f(\hat{z})^{\frac{1}{1-\theta}}$, where M^f is the distribution of operating firms, satisfies the continuity and FOSD requirements. But Assumption 3 offers other alternatives, spanning search models through pure assignment models. In the latter case, θ would instead measure the complementarity between own knowledge and the imitation opportunity. It also allows for the possibility that agents with different z draw from different distributions. We discuss various alternatives that fall under this assumption in the Appendix.

Assumptions 2 and 3 are statements only about the characterization of the equilibrium outcomes from the model, not the micro-foundations that generate them. This implies that these 3 assumptions characterize diffusion in a variety of models, including those summarized in Alvarez et al. (2008).[21] It also includes the model developed in Section 3.

5.2 Identification and Relation to Previous Quantitative Results

We now define a data-generating process that covers a class of interventions including the Brooks et al. (2018) RCT discussed in Section 2, but also includes Atkin et al. (2017), Cai and Szeidl (2018), Lafortune et al. (2018), and Fafchamps and

[20]In addition, all of the results in this section are robust to the inclusion of unobserved idiosyncratic variation via measurement error or distortions. These extensions build off an active literature on non-linear error-in-variables models (see Schennach, 2020, for a thorough review).

[21]For example, Lucas (2009) follows by setting $\beta = \rho = 1$, $c = 0$, and making F degenerate (a special case of Assumption 1), setting $\pi = z$ (Assumption 2) and assuming $\widehat{M}(\hat{z}; z, \theta) = M^\theta$ where M is the equilibrium c.d.f. of ability and θ indexes the number of draws a firm receives each period (Assumption 3). Buera and Oberfield (2020)'s delineation between random, original innovations and learning from others is a particular interpretation of θ in Assumption 3. More examples, including those that move away from random meetings, are included in the Appendix.

Quinn (2018), among others.[22] We formally define the data generating process in Assumption 4.[23]

Assumption 4. *A set of agents with profit $H_\pi(\pi)$ are observed in two consecutive periods. That set is partitioned into two subsets* **C** *and* **T** *(i.e., "control" and "treatment"), characterized by their profit distributions $H_{C,\pi}(\pi)$ and $H_{T,\pi}(\pi)$. The following conditions hold:*

(a) An individual's inclusion in **T** *and* **C** *is orthogonal to unobserved characteristics.*

(b) We cannot observe the imitation opportunity for any agent in **C**. *They are drawn from a distribution $\widehat{M}_\pi(\hat{\pi}; \pi, \theta)$.*

(c) We observe the imitation opportunity for agents in **T**. *The distribution of those profits are denoted $\widehat{H}_{T,\pi}(\hat{\pi}) \neq \widehat{M}(\hat{\pi}; \pi, \theta)$. Furthermore, a positive measure of agents interacts with a more profitable match.*

$$\int_\pi \int_{\hat{\pi}} \mathbb{1}[\hat{\pi} > \pi] d\widehat{H}_{T,\pi}(\hat{\pi}) dH_{T,\pi}(\pi) > 0.$$

(d) For any arbitrary partition of **T**, *characterized by $H^1_{T,\pi}(\pi)$ and $H^2_{T,\pi}(\pi)$, unobserved characteristics are orthogonal to partition assignment.*

Assumption (a) is the usual exclusion restriction. It puts restrictions on how the unobserved characteristics vary between control and treatment. (b) formalizes the intuitive notion that we cannot observe individual-level imitation opportunities for control agents, but that matches continue to happen in the background of the economy. That is, the control group does not stop receiving imitation opportunities because of the intervention.

Assumptions (c) and (d) lay out what we require from the treatment. (c) formalize that the treatment shocks the source distribution from $\widehat{M}$ to $\widehat{H}_T$. (d) then states a second exclusion restriction within the treatment group, guaranteeing that a comparison between any two sets of treated firms is unbiased.

Our experiment in Kenya satisfies these conditions. We randomize into control and treatment to satisfy (a). (b) is assumed. The randomization of the exact matches within the treatment satisfies (c) and (d). These two layers of randomization played an important role in our estimation earlier and, as will be shown below, are critical here as well.

[22] Experimental variation is not critical. Any instrument or instruments that satisfy Assumption 4 will apply similarly. Most available evidence comes from randomized controlled trials here, so we generally focus discussion in those terms.

[23] Note that Assumption 4 is not designed to be an idealized experiment to estimate a diffusion model. One could easily develop a more useful experiment than we assume here. This is not our goal. Our goal is to understand how a particular type of experiment that has been considered in the literature relates to a class of diffusion models outlined in Section 5.1. Assumption 4 is the formalization of the way in which we tie our hands to a particular type of variation.

5.3 Identifying Diffusion Parameters

Our goal is to show that under these assumptions, we can use the same procedure as before to estimate the three diffusion parameters β, ρ, and θ. As before, we start with the generalized meeting-learning frontier.

The Meeting-Learning Frontier Defining the ATE as the percentage change in profit between firms in treatment and control,

$$ATE^{data} = \frac{\mathbb{E}[\pi_i'|i \in \mathbf{T}]}{\mathbb{E}[\pi_i'|i \in \mathbf{C}]}, \tag{5.2}$$

the model's counterpart is (letting F_T and F_C denote the distribution of unobserved shocks)

$$ATE^{model} = \frac{\mathbb{E}_T[\pi']}{\mathbb{E}_C[\pi']} = \frac{\int\int\int e^{c+\varepsilon} z^\rho \max\left\{1, \hat{z}/z\right\}^\beta d\widehat{H}_T(\hat{z}) dH_T(z) dF_T(\varepsilon)}{\int\int\int e^{c+\varepsilon} z^\rho \max\left\{1, \hat{z}/z\right\}^\beta d\widehat{M}(\hat{z}; z, \theta) dH_C(z) dF_C(\varepsilon)}. \tag{5.3}$$

The only difference between (5.3) and our baseline model is that we replace our specific meeting function $M^{f,1/(1-\theta)}$ with the more general $\widehat{M}$. Yet we assume that $\widehat{M}$ retains two key features from our baseline model: it is continuous and θ shifts the distribution. Therefore, Proposition 2 summarizing the meeting-learning frontier follows without much change. We summarize in Proposition 3.

Proposition 3. *For a given pair (β, ρ) there is at most one θ such that $ATE^{model} = ATE^{data}$. If $ATE^{data} \in [\Gamma^{min}, \Gamma^{max}]$ that θ exists and is unique. It solves*

$$ATE^{data} = \frac{\int\int \pi^\rho \max\left\{1, \hat{\pi}/\pi\right\}^\beta d\widehat{H}_{T,\pi}(\hat{\pi}) dH_{T,\pi}(\pi)}{\int\int \pi^\rho \max\left\{1, \hat{\pi}/\pi\right\}^\beta d\widehat{M}_\pi(\hat{\pi}; \pi, \theta) dH_{C,\pi}(\pi)}. \tag{5.4}$$

If $ATE^{data} \notin [\Gamma^{min}, \Gamma^{max}]$ then no such θ exists. The bounds are given by

$$\begin{aligned}
\Gamma^{min} &= \inf_\theta \frac{\int\int \pi^\rho \max\left\{1, \hat{\pi}/\pi\right\}^\beta d\widehat{H}_{T,\pi}(\hat{\pi}) dH_{T,\pi}(\pi)}{\int\int \pi^\rho \max\left\{1, \hat{\pi}/\pi\right\}^\beta d\widehat{M}_\pi(\hat{\pi}; \pi, \theta) dH_{C,\pi}(\pi)} \\
\Gamma^{max} &= \sup_\theta \frac{\int\int \pi^\rho \max\left\{1, \hat{\pi}/\pi\right\}^\beta d\widehat{H}_{T,\pi}(\hat{\pi}) dH_{T,\pi}(\pi)}{\int\int \pi^\rho \max\left\{1, \hat{\pi}/\pi\right\}^\beta d\widehat{M}_\pi(\hat{\pi}; \pi, \theta) dH_{C,\pi}(\pi)}.
\end{aligned}$$

Proposition 3 holds for any meeting technology satisfying Assumption 3, generalizing away from our specific choices in previous sections. As before, it relies on randomization between control and treatment (Assumption 4(a) on the data-generating process). This guarantees unobservable shocks ε do not show up in the estimating equation (5.4).

As before, the meeting-learning frontier delivers the same crucial constraint on the relationship between meeting and learning, requiring that they co-vary positively whenever the intervention delivers better matches than would otherwise be available.

A second interpretation of this proposition is that Proposition 3 shows the cost of mis-specifying the model. Bias in learning creates bias in meeting, though remains consistent with the observed ATE. Yet we know from Section 4 that aggregate outcomes are not independent of their relative importance.

Measuring Learning Parameters within Treatment Since Proposition 3 estimates a function $\theta(\beta, \rho)$ we need to still estimate β and ρ. As before, we utilize the variation within treatment, formalized here in 4(d). The result is summarized in Proposition 4.

Proposition 4. *The parameters (β, ρ) are identified by coefficients from the regression run only on treated agents (all $i \in \mathbf{T}$)*

$$\log(\pi_i') = \widetilde{c} + \rho \log(\pi_i) + \beta \log\left(\max\left\{1, \frac{\hat{\pi}_i}{\pi_i}\right\}\right) + \varepsilon_i, \tag{5.5}$$

where $\widetilde{c}$ is the constant equal to the technological parameter c if $\pi = z$. The estimated coefficients $(\hat{\beta}, \hat{\rho})$ are equal to their structural counterparts.

The main difficulty with attempting to estimate (5.5) is that unobservable shocks enter into it. If different sets of treated firms draw unobservable ε shocks from different distributions, the estimates from (5.5) are likely biased.

There are two ways to solve this problem. The first is to specific a more complete model and lean on that structure to derive estimates. The second, which we use, is to lean more on the structure of the data. The within-treatment randomization guarantees $(\hat{\beta}, \hat{\rho})$ remain unbiased without resorting to additional model structure. Without it, we would likely be required to narrow the set of models to which this approach can be applied.

To summarize, there is substantial evidence that diffusion plays an important role in the development process, derived from both micro and macro sources. Changing opportunities to meet, and therefore learn from, others at scale requires understanding how to use these RCT estimates to build evidence. We show that regardless of the specifics of the exact economy one has in mind, there exist simple additional moments that can be measured in these RCTs that help discipline what we should expect to find at scale. The link between these moments and underlying model structure relies in large part on the same flexibility that randomization offers empirical work. It allows us to difference out unobservable characteristics – here, model structure – that would otherwise interact with the diffusion block of the model. This guarantees the same identification procedure holds under a broader class of models than the specific one developed in Section 3.

5.4 Further Discussion and Additional Appendix Results

Before concluding, we discuss some additional theoretical and quantitative results that are available in the Appendix.

In terms of the generalized procedure developed in Section 5 to determine diffusion parameters, we show that it accommodates additional features. First, we allow a more general law of motion for ability which can be estimated semi-parametrically with the same data generating process. Second, and relatedly, the results can be extended to include heterogeneous returns by characteristics. Third, we extend the results to a more general relationship between observables and ability that allows for the integration of production function estimation. Fourth, we show the procedure can be adjusted to include measurement error or idiosyncratic distortions that affect the relationship between profit and ability, building off an active literature on non-linear error-in-variables models (see Schennach, 2020, for a thorough review). These various adjustments introduce important considerations and complications, such as issues of power for non-parametric estimation or the introduction of the required deconvolution methods to deal with measurement error. The underlying economic intuition holds without much change however, and we focus in the main text on this relatively parsimonious set of parameters for this reason.

In terms of the quantitative results in Sections 3 and 4, we also add a number of extensions in the Appendix. First, we quantify the bias induced by mis-measured profit. Our results are a lower bound on the equilibrium gains. Idiosyncratic distortions or non-deterministic supplier search naturally generate a similar, but not identical, result. Second, we solve the social planner's problem to study the gains that could be achieved by transitioning the economy to its efficient allocation. We find that welfare gains are largest at intermediate levels of β. The results deliver a similar message as the main text: measuring the various forces that inform aggregate gains is critical. Third and finally, we use the work of Cai and Szeidl (2018) to apply our results to a different experiment. This experiment offers a useful comparison to our results in the main text: they find that gains from matches persist longer than in our baseline RCT, and also provide direct evidence of diffusion within matches. We replicate the persistence of their treatment effect. The reason is because our estimation procedure infers different parameters from different patterns of covariance within treated firms.

6 Conclusion

We develop a model to study the cost of frictions that limit potentially profitable interactions between firms. We discipline the model by linking it to a promising set of micro-level interventions that offer these same opportunities at a smaller scale. Using evidence from an RCT in Kenya, we find that equilibrium income rises by 11 percent off an average treatment effect of 19 percent. The discipline on that 11 percent increase in income comes primarily from moments other than the average treatment effect. Our results point to other moments that do. In particular, we show that a covariance moment plays a critical role in generating equilibrium gains at scale. This moment can be estimated with partial equilibrium RCT results, thus providing policy-relevant information on scalability. The results highlight the important complementarity between causal interventions and aggregate models (Buera et al., 2022).

The results also open up additional questions for future work. We leave out features such as firms that are unwilling to share information due to competition, though we show in the Appendix that some versions of this idea are feasible under our framework. One could always write down a more complicated model with such a feature. That part is easy. But adding model features demands more empirical moments for estimation. This requires more subtly and targeted variation in designing interventions that speak to these features of the environment. Different field experiments, designed with an eye toward aggregate theory, could further refine our understanding of key aggregates governed by a number of difficult-to-measure elasticities that affect diffusion at scale.

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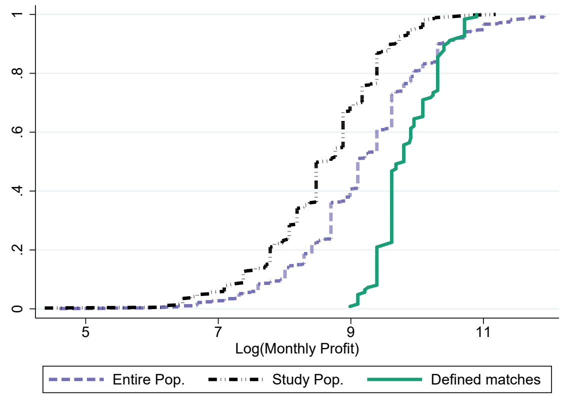
Table of Contents for Online Appendix

A Additional Details from the Main Text

A.1 RCT: Baseline Profit Distributions

Figure 6: Baseline Profit Distributions



A.2 RCT: Balance Tests

Our basic balance check is

$$y_{i0} = \alpha_0 + \alpha_1 \mathbf{T}_i + \varepsilon_i,$$

where y_{i0} is the baseline outcome for individual i and $T_i = 1$ if i is eventually treated. Those results are in Table 4.

We conduct the second balance test

$$y_{i0} = \alpha_0 + \sum_{j=L,M,H} \alpha_j \mathbf{T}_{ij} + \varepsilon_i$$

where the indicator now depends on whether firm i is a treatment firm matched with a bottom 25th percentile (denoted M_{iL}), 25-75 percentile (T_{iM}), or top 25 percentile firm (T_{iH}) in terms of baseline profitability.[24] Table 5 reports the results. The only significant difference is in age, and the magnitude is small.

A.3 RCT: Empirical Impact on More Productive Member of the Match

Since the more productive members of treatment matches were not randomly selected, we require a different approach to identify any effect on these business owners. Brooks

[24]We have experimented with a number of different ways to compute the balance table, and all show the same results.

Table 4: Balance Test from (from Brooks et al., 2018)

	Control Mean	Mentor - Control
	(1)	(2)
Firm Scale:		
Profit (last month)	10,054	-975.25
		(1186.76)
Firm Age	2.39	-0.05
		(0.23)
Has Employees?	0.21	-0.02
		(0.05)
Number of Emp.	0.21	0.02
		(0.06)
Business Practices:		
Offer credit	0.74	-0.02
		(0.06)
Have bank account	0.30	-0.03
		(0.06)
Taken loan	0.14	-0.05
		(0.04)
Practice accounting	0.11	0.00
		(0.04)
Advertise	0.07	0.04
		(0.03)
Sector:		
Manufacturing	0.04	-0.03
		(0.02)
Retail	0.69	0.03
		(0.06)
Restaurant	0.14	-0.02
		(0.05)
Other services	0.17	0.06
		(0.05)
Owner Characteristics:		
Age	29.1	-0.25
		(0.64)
Secondary Education	0.51	-0.00
		(0.06)

Table Notes: Columns 1-2 are the coefficient estimates from the regression $y_i = \alpha + \beta T_i + \varepsilon_i$, where T_i is an indicator for treatment. Column 1 is $\widehat{\alpha}$. Statistical significance at 0.10, 0.05, and 0.01 is denoted by *, **, and, ***.

et al. (2018) details these results, but Figure 7 reproduces some key results for simplicity's sake. Figure 7 suggests no statistically discernible discontinuity around the cutoff.

We next test this more formally. In particular, letting $\overline{\varepsilon}$ be the cut-off value for mentors, we run the regression

$$\pi_i = \alpha + \tau D_i + f(N_i) + \nu_i \tag{A.1}$$

Table 5: Balancing Test at Baseline

	Control Mean (1)	T_L - Control (2)	T_M - Control (3)	T_H - Control (4)
Firm Scale:				
Profit (last month)	10,054	-732.65	-1337.06	-760.08
		(1314.56)	(1393.38)	(2128.41)
Firm Age	2.39	0.04	-0.19	0.08
		(0.28)	(0.30)	(0.46)
Has Employees?	0.25	-0.10	-0.07	0.10
		(0.07)	(0.07)	(0.11)
Number of Emp.	0.23	-0.05	0.00	0.18
		(0.08)	(0.08)	(0.13)
Business Practices:				
Offer credit	0.74	-0.07	0.04	-0.03
		(0.07)	(0.08)	(0.12)
Have bank account	0.30	-0.04	-0.05	0.06
		(0.07)	(0.08)	(0.12)
Taken loan	0.14	-0.07	-0.06	0.03
		(0.05)	(0.05)	(0.08)
Practice accounting	0.01	-0.01	0.01	-0.01
		(0.01)	(0.02)	(0.02)
Advertise	0.07	0.04	0.01	0.11
		(0.05)	(0.05)	(0.07)
Sector:				
Manufacturing	0.04	-0.02	-0.04	-0.04
		(0.02)	(0.03)	(0.04)
Retail	0.69	-0.03	0.00	-0.10
		(0.08)	(0.08)	(0.12)
Restaurant	0.14	-0.06	0.00	0.03
		(0.05)	(0.06)	(0.09)
Other services	0.17	0.09	0.02	0.07
		(0.06)	(0.07)	(0.10)
Owner Characteristics:				
Age	29.1	0.92	-1.88	0.50
		(0.79)	(0.84)**	(1.28)
Secondary Education	0.51	0.02	-0.08	0.13
		(0.08)	(0.09	(0.13)

Table notes: Columns 1-4 are the coefficient estimates from the regression above, with column one being the estimate of the constant $\widehat{\alpha}_0$. Statistical significance at 0.10, 0.05, and 0.01 is denoted by *, **, and, ***. All constants are significant at one percent.

where π_i is profit, $D_i = 1$ if individual i was chosen as a mentor ($\widehat{\varepsilon}_i \geq \overline{\varepsilon}$, $f(N_i)$ is a flexible function of the normalized running variable $N_i = (\widehat{\varepsilon}_i - \overline{\varepsilon})/\sigma_\varepsilon$, and ν_i is the error term. The parameter τ captures the causal impact of being chosen as a mentor. We use local linear regressions to estimate the treatment effects on profit and inventory, along with business practices of record keeping and marketing. The results are in Table 6, and we find that being a mentor has no statistically significant effect on profits. Moreover, there is no change in marketing or record-keeping practices, which

Figure 7: Profit for mentors and non-mentors (from Brooks et al., 2018)

(a) Full sample (b) IK Optimal Bandwidth

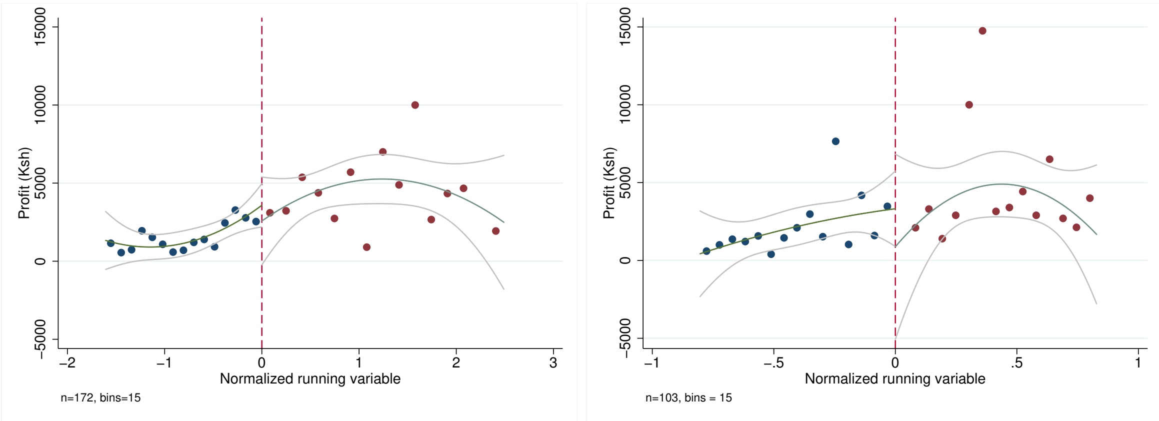


Figure notes: Figure 7 plots profit along with a fitted quadratic and its 95 percent confidence interval. Figure 7a uses the entire sample, while Figure 7b uses the Imbens and Kalyanaraman (2012) procedure to choose the optimal bandwidth. Both use 15 bins on either side of the cutoff.

one might associate with ability. There is some evidence that inventory spending decreases, but it cannot be statistically distinguished from zero. Overall, we find little evidence that entering into a match changes either business scale or business practices for the more productive member of the match. This is consistent with the max function in the forward equation for ability (equation 5.1), which is assumed here and in much of the existing literature.

Table 6: Regression discontinuity results for matched firm treatment effect (Brooks et al., 2018)

Percent of IK optimal bandwidth	Scale		Practices	
	Profit	Inventory	Marketing	Record keeping
100	-503.18	-3105.87	0.01	0.02
	(1321.82)	(2698.11)	(0.11)	(0.18)
150	300.19	-2585.22	0.01	0.07
	(1407.26)	(2291.34)	(0.09)	(0.14)
200	322.09	-123.59	0.01	0.10
	(1324.17)	(1964.08)	(0.08)	(0.13)
Treatment Average	4387.34	8435.79	0.08	0.85
Control Average	1794.09	4039.20	0.13	0.63

Table notes: Statistical significance at 0.10, 0.05, and 0.01 is denoted by *, **, and, ***. Profit and inventory are both trimmed at 1 percent.

A.4 Model: Increasing θ to match RCT treatment effect

In the main text, we increase θ from $\theta = -0.417$ to $\theta = -0.063$. We replicate the results here under a different quantitative experiment: we increase θ such that the policy change induces the same partial equilibrium effect in the model as in our empirical results. Specifically, we create a treatment and control group identical to our empirical RCT. We then shock the treatment group by allowing them to draw from a new source distribution $\widehat{M}(\hat{z};\theta^T)$ instead of $\widehat{M}(\hat{z};\theta)$. We set θ^T such that running the RCT in the model delivers an identical treatment effect to our empirical results.[25] This implies that θ increases to $\theta = 0.512$.

Table 9 replicates Table 3 from the main text under this different quantitative experiment.

Table 7: Equilibrium Moments

	(1) Baseline	(2) Fixed Wage	(3) New Equilibrium
Income	1.00	1.35	1.59
Ability	1.00	1.38	1.67
Aggregate Labor Supply	1.00	0.63	0.90
Wage	1.00	1.00	1.76

Table notes: Column (1) is the initial equilibrium, normalized to one. (2) and (3) report the new stationary equilibrium after shocking the matching technology, where (2) holds the wage fixed at its baseline level and (3) allows it to adjust.

Overall, average income rises by 59 percent. When we decompose the aggregate change, 57 percent of the total ability change comes from the direct effect on ability (Column 2) and the remaining comes from the amplification through the wage. Similarly for income, the direct effect accounts for 59 percent. The mechanisms for these changes are discussed in the main text. Note, however, that these results point to a larger role for price amplification (i.e., the price amplification accounts for 41 percent of the average income gain here and 37 percent in the main text). This occurs because the induced wage change is convex in the imposed θ change. Thus, the results point to a larger role for price amplification as the aggregate policy change becomes larger.

[25] In the empirics, we let treated firms draw from the source distribution $\widehat{H}_T$. The idea is the same, but does not require the treatment source distribution to be in the same functional class as $\widehat{M}$.

B Examples of Different Matching Processes

In the main body of the paper, we provided two examples of matching processes that fall under our assumptions, and we detail additional versions here.

B.1 Noise in the Imitation Process

An agent with ability z receives new arrivals of ideas that have two components: z_m that comes from a random match from another agent, and γ a random innovation on that idea. Then $\hat{z} = \gamma^{1/\theta} z_m$. Here, z_m is a uniform draw from the distribution of productivities. Then if γ has a cumulative density function given by Γ, then:

$$\widehat{M}(c) = Prob(\hat{z} \leq c) = Prob(z_m \leq c\gamma^{-1/\theta}) = \int M(c\gamma^{-1/\theta}) d\Gamma(\gamma) \tag{B.1}$$

B.2 Effort Choice and Bargaining

Each period, every agent characterized by ability z is matched to an agent that owns a potential imitation opportunity z_m as a uniform draw from the distribution of operating firms M. The agent has an effort endowment of 1 that must be divided between imitation and providing a utility benefit to the owner of the imitation opportunity z_m. If $z \geq z_m$, then no effort is put into imitation and $\hat{z} = z$. If $z_m > z$, then the agent and the owner of the imitation opportunity must first agree on the distribution of effort, then the choice of effort x and the values of z and z_m together generate the value of $\hat{z}$ for the agent in that period according to:

$$\hat{z} = \left(\frac{z_m}{z}\right)^x z \tag{B.2}$$

That is, by putting in more effort $x \in [0, 1]$ the agent is able to close the gap between their z and z_m. The benefit to the owner of z_m is given by the function $b(x)$, which is decreasing in x.

Agents and owners of imitation opportunities have one-off interactions and each receive 0 benefit if no agreement is made. They bargain over the assignment of the agent's effort between imitation and utility benefits for the owner of the imitation opportunity according to a Nash bargaining problem where the bargaining weight of the agent is θ. The bargaining problem is:

$$\max_{x\in[0,1]} \left(\left[\frac{z_m}{z}\right]^x z\right)^\theta b(x)^{1-\theta} \tag{B.3}$$

Suppose that $b(x)$ is given by $b(x) = 1 - x$. Then it is easy to show that:

$$x = \max\left[0, 1 - \frac{1-\theta}{\theta \log(z_m/z)}\right] \tag{B.4}$$

$$\hat{z} = \max\left[z, z_m e^{1-1/\theta}\right] \tag{B.5}$$

As expected, the more bargaining power that the learning agents have, the greater is x, resulting in greater $\hat{z}$.

Note that, in the model, draws of imitation opportunities $\hat{z} < z$ are not useful. Hence, the distribution $\widehat{M}$ can be written, for any value c, as:

$$\widehat{M}(c) = Prob(\hat{z} \leq c) = Prob(z_m e^{1-1/\theta} \leq c) = Prob(z_m \leq c e^{1/\theta-1}) = M(c e^{1/\theta-1}) \tag{B.6}$$

or following the notation more standard in the paper:

$$\forall z, \widehat{M}(\hat{z}; z, \theta) = M(\hat{z} e^{1/\theta-1}) \tag{B.7}$$

B.3 Deterministic Assignment

Here we consider a case where $\widehat{M}$ arises when all agents can interact with one another and sort into relationships endogenously. Suppose that every agent with ability $\hat{z}$ has the option to influence any other agent that has ability z. Every agent can only be influenced by one other agent each period, and they always prefer to be influenced by the highest ability possible.

The utility of an agent with ability $\hat{z}$ influencing an agent with ability z is given by:

$$\frac{\hat{z}}{z} - 1 - \frac{1}{2\theta}\left(\frac{\hat{z}}{z} - 1\right)^2 \tag{B.8}$$

That is, the agent with $\hat{z}$ gains benefit in proportion to how large the benefit is for the other agent, but their cost is quadratic in the distance between their productivities. For example, the influencer is happy when the other agent is helped by their influence, but it takes more effort to influence when the distance between them is great. Therefore, if there is a continuous distribution of $z < \hat{z}$, the ideal agent that the influencer would like to interact with has ability:

$$z^*(\hat{z}) = \hat{z}/(1+\theta) \tag{B.9}$$

That is, the lower is the cost of influencing low ability firms, the deeper into the left tail of the distribution is the agent willing to go.

However, since every agent can only be influenced by one agent each period and they strictly prefer to be influenced by agents of higher ability, it is possible that (even if the distribution is continuous) that the ideal agent for $\hat{z}$ is already matched to another influencer. Therefore, intuitively, the probability distribution over assignment between $\hat{z}$ and z is constructed by starting at the upper support of the distribution M, allowing the highest ability firms to choose their most preferred matches, then descending down through the distribution letting each firm choose to influence its preferred firm among those remaining. Note that not all firms need have another firm to influence if their utility from doing so be negative.

Formally, the probability distribution over imitation opportunities can be constructed in the discretized case as follows, when the ability grid takes values $z \in \{z_1, ...z_N\}$, which are ordered ($i < j \implies z_i < z_j$).

Define $\tilde{\mu}(z, \hat{z})$ as the measure of $\hat{z}$ influencing z (a $N \times N$ matrix). We can construct $\tilde{\mu}$ in the following steps given the measure μ of agents of each z type:

1. Let $U(z, \hat{z})$ be the $N \times N$ matrix of utilities of $\hat{z}$ influencing z, and $\tilde{\mu}$ be a $N \times N$ matrix of zeros. Let $\bar{\mu}$ be the $N \times 1$ vector of unassigned influencers and μ_u be the $N \times 1$ vector of unassigned imitators. Set $\bar{\mu} = \mu_u = \mu$, $n = N$, and $m = 1$.

2. Let l be the m-argmax of $U(\cdot, z_n)$. If $U(z_l, z_n) \leq 0$, set $\tilde{\mu}(z_1, z_n) = \mu_u(z_n)$ and skip to step 5.

3. If $\bar{\mu}(z_n) \leq \mu_u(z_l)$, then $\bar{\mu}(z_n) = 0$, $\mu_u(z_l) = \mu_u(z_l) - \bar{\mu}(z_n)$, and $\tilde{\mu}(z_l, z_n) = \bar{\mu}(z_n)$. Skip to step 5. Otherwise, go to 4.

4. If $\bar{\mu}(z_n) > \mu_u(z_l)$, then set $\tilde{\mu}(z_l, z_n) = \mu_u(z_l)$, $\mu_u(z_n) = 0$ and $\bar{\mu}(z_n) = \bar{\mu}(z_n) - \mu_u(z_l)$. Set $m = m + 1$ and return to step 2.

5. Set $n = n - 1$ and $m = 1$. If $n = 0$, go to step 6. Otherwise, go to step 2.

6. Set $\tilde{\mu}(\cdot, z_1) = \tilde{\mu}(\cdot, z_1) + \mu_u$, and stop.

Given this matrix $\tilde{\mu}(z, \hat{z})$, the measure of assignments $\widehat{M}$ is given by:

$$\widehat{M}(\hat{z}_i, z_j) = \frac{\sum_{k=1}^{i} \tilde{\mu}(z_j, \hat{z}_k)}{\mu(z_j)}$$

B.4 Cost to Receive a Match

Firms pay a cost to receive a uniform random draw from the productivity distribution. We model this as a function $f(s;\theta)$, in that a firm that pays cost $f(s;\theta)$ receives a uniform random draw with probability s. We assume that $f_\theta > 0$, so that the cost to achieve any level of s is increasing in θ. In a stationary equilibrium, under standard conditions this implies a stationary decision rule $s(z, M^*;\theta)$ with $s_\theta < 0$. We can write the distribution of draws as

$$\begin{aligned} \widehat{M}(c; z, \theta) &= (1 - s(z, M^*;\theta)) + s(z, mM^*;\theta)M^*(c) \\ &\equiv Q(c; z, M^*, \theta) \end{aligned}$$

Thus, in the stationary equilibrium of this economy, our same procedure goes through. This example provides important context for our set of assumptions – they need not be assumptions only on the primitives of the model. Additional assumptions, such as stationarity, may guarantee the model is covered under our assumptions. The use of stationarity here is similar to its role in the identification procedure of Jarosch et al. (2021), who study learning among German co-workers.

C Extensions of Diffusion Parameter Identification

In this Appendix, we focus on theoretical extensions of the main estimation procedure in the paper to show that the procedure itself is robust to any number of extensions. In Appendix E, we provide a quantitative evaluation of a particular extension related to mis-measurement.

C.1 Semi-parametric identification

Assumption 1 laid out a function form for the law of motion of ability: $z'(z, \varepsilon, \hat{z}) = e^{c+\varepsilon} z^{\rho} \max\left\{1, \frac{\hat{z}}{z}\right\}^{\beta}$. We broaden this in Assumption 5 by replacing the max function,

Assumption 5. *Given ability z this period, an imitation opportunity $\hat{z}$, and a random shock ε, ability next period z' is given by*

$$z'(z, \varepsilon, \hat{z}) = e^{c+\varepsilon} z^{\rho} f\left(\frac{\hat{z}}{z}\right) \tag{C.1}$$

Assuming $f(\hat{z}/z) = \max\{1, (\hat{z}/z)\}^{\beta}$ gives us the original Assumption 1. Proposition 5 summarizes that we can instead estimate the function f using the same data-generating process as in the main text.

Proposition 5. *The data-generating process of Assumption 4 identifies (ρ, f) in equation (C.1) (while maintaining Assumptions 2 and 3 in the main text) by estimating the regression*

$$\log(\pi_i') = \tilde{c} + \rho \log(\pi_i) + f\left(\frac{\hat{\pi}_i}{\pi_i}\right) + \varepsilon$$

This result follows directly from an established literature on partially linear regressions. See, for instance, Yatchew (1997) on differencing estimators in this class of models.[26] Härdle et al. (2000) provides a detailed review.

C.2 More general relationship between observables and z

In Assumption 2 we assume that some observable (e.g., profit) π has the characteristic that $\pi \propto z$. We extend that here.

[26] The basic idea is that by ordering the data such that $\hat{\pi}_1/\pi_1 < \hat{\pi}_2/\pi_2 \ldots < \hat{\pi}_N/\pi_N$, once can difference out the nonlinear f in the limit under conditions that guarantee that the gap between i and $i+1$ goes to zero. This allows straightforward OLS to estimate ρ. Then f can be estimated non-parametrically by any number of methods.

Assumption 6. *There exists a known function* $g : \mathbf{X} \to \mathbb{R}_{++}$ *that maps observable characteristics* $\mathbf{x}$ *to ability* z *up to a potentially unknown constant of proportionality. That is,* $g(\mathbf{x}) = Cz$ *for some potentially unknown constant* C*.*

By assuming $\pi \in \mathbf{x}$ and $g(\mathbf{x}) = \pi$, we recover the original assumption $\pi \propto z$. But Assumption 6 allows for more complicated possibilities. For example, one could estimate a production function using the control group panel data. Such a procedure would imply a mapping $g(y, n, k) = Cz$. That is, it takes output data y and input data for labor and capital (n, k) (or any other input bundle) and infers the value z.[27]

Proposition 6. *The parameters* (β, ρ, θ) *are identified when we replace Assumption 2 with Assumption 6.*

This follows almost directly, as the regression

$$\log(g(\mathbf{x}')) = c + \rho \log(g(\mathbf{x})) + \beta \log \left(\max \left\{ 1, \frac{g(\hat{\mathbf{x}})}{g(\mathbf{x})} \right\} \right) + \varepsilon,$$

is straightforwardly estimated with known g. By Assumption 6 this collapses to the required equation that gives (β, ρ). The second step goes through with the same adjustment. The key to our procedure is not the proportionality of any one variable with z, but a proportional mapping between *any* set of observables and z.

C.3 Mis-measurement

We now assume that profit is mis-measured. This affects our estimation procedure, introducing bias into the parameters. The regression error is not additively separable from the true value in our non-linear model, which implies that standard instrumental variable methods to correct linear measurement error no longer hold. Yet, there is a substantial and active literature on mis-measurement in non-linear models that provides a number of ways to overcome this issue.

We discuss this issue in the context of a more general ability law of motion, to emphasize that it does not depend on the specific choices we have made on functional forms. We provide a quantitative evaluation of these issues in Appendix E.

[27] g is not the production function here, but is inferred from it.

Assumption 7. *The law of motion for diffusion can be written as*

$$log(\pi') = \sum_{j=1}^{M} \beta_j g_j(\vec{\pi}) + \varepsilon$$

where $\vec{\pi} = (\pi, \hat{\pi})$ *for a known function* $(g_j)_{j=1}^{M}$.

Note that we have already imposed the maintained ability to move between ability z and profit π. The key additional assumption is an adjustment to Assumption 4, which governs the type of data to which we have access.

Assumption 8. *Profit is measured with error, and we observe two outcomes that are mis-measured versions of the true value,* $\vec{\pi}^* = (\pi^*, \hat{\pi}^*)$. *We denote* $\vec{\pi}^k$ *as the two entries in the vector. We denote these observable values as* $(\pi_1^k, \pi_2^k), k = 1, 2$. *The measurement error is classical, so that for each individual* i *we observe*

$$\begin{aligned} \vec{\pi}_{1i}^k &= \vec{\pi}_i^{*k} + \nu_{1i}^k, \quad k = 1, 2 \\ \vec{\pi}_{2i}^k &= \vec{\pi}_i^{*k} + \nu_{2i}^k, \quad k = 1, 2 \end{aligned}$$

where ν_1 *and* ν_2 *are unobserved disturbances. We assume the following relationships between the measurement error and true values:*

$$\begin{aligned} &\mathbb{E}[\nu_1^k | \pi^{*k}, \nu_2^k] = 0, \quad k = 1, 2 \\ &\nu_2^k \textit{ is independent from } \vec{\pi}^*, \nu_2^{-k}, \textit{ where } -k \neq k \end{aligned}$$

The assumption of a repeated measurement opens up a suite of tools related to repeated measurement adjustments in non-linear estimation. While other methods exist to solve this problem, the existence of this approach has the benefit of almost always being available in a firm-level survey.[28]

The basic idea behind this identification approach comes from Kotlarski's Lemma, which in $\mathbb{R}^1$ is

$$\phi_{\pi^*}(t) = \exp\left(\int_0^t \frac{\mathbb{E}[i\pi_1 e^{it\pi_2}]}{\mathbb{E}[e^{it\pi_2}]} \right)$$

and $\phi_{\pi^*}(t)$ is the characteristic function $\phi_{\pi^*}(t) = \int_{\mathbb{R}} e^{it\pi^*} f_{\pi}^*(\pi^*)dx$. An inverse Fourier transform gives us the distribution of true values f_{π^*}, which can be used to construct

[28] For example, π_1 could be profit asked directly while π_2 could be measured as revenue minus costs. Another would be to use the same variable measured at two points in time, as highlighted by Schennach (2020). Finally, many models allow relationships between input expenditures, revenue, and profit that could be utilized, albeit with more structure than we have here. An example is a Cobb-Douglas production function with competitive factor markets.

the relevant estimator moments.

Our model requires $\vec{\pi}^* = (\pi^*, \hat{\pi}^*) \in \mathbb{R}^2$, which introduces some complications. The second part of Assumption 8 provides necessary conditions for identification in a multidimensional nonlinear model.

Proposition 7. *If $\mathbb{E}[|\vec{\pi}^k|]$ and $\mathbb{E}[|\eta_1^k|]$ are finite, then there exists a closed form for any function $\mathbb{E}[u(\vec{\pi}^*, \beta)]$ whenever it exists.*

Proof. Provided in Schennach (2004). ∎

Schennach (2004) provides the details of the approach and how to develop an estimator from Proposition 7. The key feature, however, is that this result allows a broad class of extremum estimators to be deployed to identify β.

C.4 Additional characteristics

One might also suspect that alternative characteristics influence learning. For example, firm owners may retain more ability when meeting with another owner of a similar age. This amounts to allowing β to depend on a set of characteristics of the firm owner $\mathbf{x}$ and her match $\hat{\mathbf{x}}$. In this case, we can write

$$\log(\pi_i') = c + \rho \log(\pi_i) + \beta(\mathbf{x}, \hat{\mathbf{x}}) \log\left(\max\left\{1, \frac{\hat{\pi}_i}{\pi_i}\right\}\right)$$

or, binning characteristics $\mathbf{X} \times \hat{\mathbf{X}}$ in some way,

$$\log(\pi_{ib}') = c + \rho \log(\pi_{ib}) + \sum_{b=1}^{B} \beta_b \log\left(\max\left\{1, \frac{\hat{\pi}_{ib}}{\pi_{ib}}\right\}\right)$$

This regression identifies $(\rho, \beta_1, \ldots, \beta_B)$ under the same assumptions as in the main text. The second step follows with a slight adjustment to Assumption 3. We assume there is a discrete distribution over types Γ_b and, with a slight abuse of notation, re-write the draws over types and profit as

$$\widehat{M}(\hat{z}, b; z, \theta) = \widehat{M_b}(\hat{z}; z, \theta)\Gamma_b$$

As long as $\widehat{M_b}$ has the same properties as Assumption 3, the second step of the procedure similarly identifies θ.

D Characterizing the Efficient Allocation from the Social Planner's Problem

Here, we lay out the solution to the social planner's problem, and show that it similarly relies on properly measuring the intensive and extensive margins.

Before doing so, one conceptual issue to deal with is the role of suppliers. We exclude them from our measure of welfare. In our context, these suppliers take their profits out of Dandora, so that buying intermediates does indeed involve resources exiting the economy. To operationalize this idea, we assume that the price paid follows the same solution as the Nash bargaining problem solved in Proposition 1, in that the price p_x is given

$$p_x = \left(\frac{1 - \eta - \nu(1 - \eta - \alpha)}{\alpha} \right) e^{-s} z^{\frac{\alpha+\eta-1}{\alpha}}.$$

We will write $p_x(z, s)$ to denote this price.[29]

With those details, we are ready to define the planner's problem. The social planner allocates occupations o, firm inputs (x, n) and supplier search intensity s for each agent to maximize *ex ante* utility, subject to the relevant aggregate resource constraints. Since we will focus on the stationary equilibrium, we drop the dependence of the decision rules on the aggregate state M for some notational simplicity. Defining the value to an agent with ability z as

$$\widetilde{v}(z) = \omega \log(c(z)) + (1 - \omega) \log(1 - s(z)) + (1 - \delta) \int_{\varepsilon} \int_{\hat{z}} \widetilde{v} \left(e^{c+\varepsilon} z^{\rho} \max \left\{ 1, \frac{\hat{z}}{z} \right\}^{\beta} \right) d\widehat{M}(\hat{z}) dF(\varepsilon),$$

we can write the planner's problem recursively as

$$\max_{o(\cdot), c(\cdot), x(\cdot), n(\cdot), s(\cdot)} \int_0^{\infty} \widetilde{v}(z) dM(z) \qquad \text{(D.1)}$$

[29] There is nothing conceptually difficult about including these suppliers in the measure of welfare. Our goal is only to remain faithful to the economic environment from which the empirics are derived. A further benefit of this assumption is that it focuses attention on the role of the diffusion externality, as opposed to other types of inefficiencies that arise from the bargaining protocol.

$$s.t. \quad \int_{o(z)=1} \Big(x(z)^{\alpha} n(z)^{\eta} - p_x(z, s(z)) x(z) \Big) dM(z) = \int_0^{\infty} c(z) dM(z) \tag{D.2}$$

$$\int_{o(z)=1} n(z) dM(z) = \int_{o(z)=0} dM(z) \tag{D.3}$$

$$M(z') = \delta G(z') + \tag{D.4}$$
$$(1-\delta) \int_0^{\infty} \int_0^{\infty} F(\log(z') - \rho \log(z) - \beta \log(\max\{1, \hat{z}/z\}) - c) d\widehat{M}(\hat{z}) dM(z)$$

$$\widehat{M}(\hat{z}; M) = \left(\frac{\int_0^{\hat{z}} \phi(z, M) dM(z)}{\int_0^{\infty} \phi(z, M) dM(z)} \right)^{\frac{1}{1-\theta}}. \tag{D.5}$$

While complicated looking, this problem has a straightforward interpretation. The planner's objective is to maximize the expected value of $\widetilde{v}$. The first two constraints are the aggregate resource constraints – (D.2) determines the resources that can be allocated to consumption, while (D.3) equalizes labor supply and demand. The latter two constraints show that the planner internalizes how her decisions affect the evolution of the aggregate state (via D.4) and the imitation opportunities that arise from it (via D.5). These constraints highlight the planner's ability to overcome the diffusion externality, in that she takes into account the implications of occupational choice on learning opportunities in a way that individual agents do not.

We measure the difference in welfare between the allocation chosen by the planner and the baseline *laissez faire* equilibrium in consumption-equivalent terms. That is, we ask by what percentage we would we have to increase each agent's consumption in every state and time period to equalize average utility between the two economies. This difference is our measure of the aggregate importance of diffusion.

While the planner's problem does not admit a closed-form solution, we can derive some implications for comparison to the baseline *laissez faire* equilibrium.

Proposition 8. *The planner chooses a cutoff rule for occupations, $\underline{z}$, such that all $z \geq \underline{z}$ operate firms. Consumption c_p is constant across agents and given by the constant returns to scale aggregate production function $c_p = A N_s^{\frac{\eta}{1-\alpha}} Z^{\frac{1-\alpha-\eta}{1-\alpha}}$, where A is a constant and the two aggregate inputs are*

$$N_s = \int_0^{\underline{z}} dM(z) \qquad , \qquad Z = \int_{\underline{z}}^{\infty} z \exp(s(z))^{\frac{\alpha}{1-\alpha-\eta}} dM(z).$$

Moreover, if $s(\underline{z}) > 0$ (which we verify at our estimated parameters), $s(\cdot)$ is a strictly increasing and concave function of the form

$$s(z) = \left(\frac{1-\alpha-\eta}{\alpha}\right) W_0 \left[\left(\frac{\alpha}{\eta+\alpha-1}\right) \exp\left(\frac{\alpha}{\eta+\alpha-1}\right) q(z/\underline{z}, s(\underline{z})) \right] + 1 \quad \forall z \geq \underline{z},$$

where $W_0(\cdot)$ is the principal branch of the Lambert W function and $q(\cdot,\cdot)$ is a function of relative ability $z/\underline{z}$ and supplier search at the cut-off value, $s(\underline{z})$.

Proof. The proof is at the end of the Appendix, in Appendix Section G. ■

One can see the goals of the planner in Proposition 8. Like in the baseline, the planner uses a cut-off rule to define occupations. As we show below, she chooses fewer firms than the baseline equilibrium, a function of the diffusion externality in the baseline economy. Furthermore, she shifts the search for suppliers away from relatively low ability agents. Instead, she takes advantage of complementarity between ability and supplier search effort. This allows higher ability agents to procure resources that can be redistributed to all agents. These incentives are naturally absent in the baseline equilibrium, where individuals consume their income.

In terms of our inability to push further theoretically, the properties of W_0 preclude a closed form solution.[30] We derive these results in Appendix G.5, and proceed with quantitative results in the next section.

D.1 Quantitative Implications

Our interest here is understanding the importance of separately identifying the intensive and extensive margin parameters to understand the welfare gains in the social planner's problem.

We follow a similar (but slightly simpler) approach to the main text. We exogenously vary β, then re-estimate θ to continually match the same average treatment effect. Thus, the average treatment effect is still used as an estimating moment, but our first stage regression (run within the treatment group) is not.

Throughout, we hold the persistence ρ fixed for simplicity. Figure 8 plots the implied value of θ and the consumption-equivalent welfare gains, the latter of which

[30] The Lambert W function is the inverse of $F : x \mapsto x\exp(x)$, and we can restrict attention to the principal branch. The main issue for our purposes is that the only analytical characterization of W_0 is the power series $W_0(a) = \sum_{n=1}^{\infty}((-n)^{n-1}/n!)a^n$, which is of little help in attempting to attain a closed form for the planner's problem here. Put slightly more technically, the supplier search function s is the solution to a delay differential equation in z, but this solution prevents an analytic characterization of the initial condition $s(\underline{z})$.

is normalized to one at our estimated value.

Figure 8: Importance of Separately Identifying Two Diffusion Effects

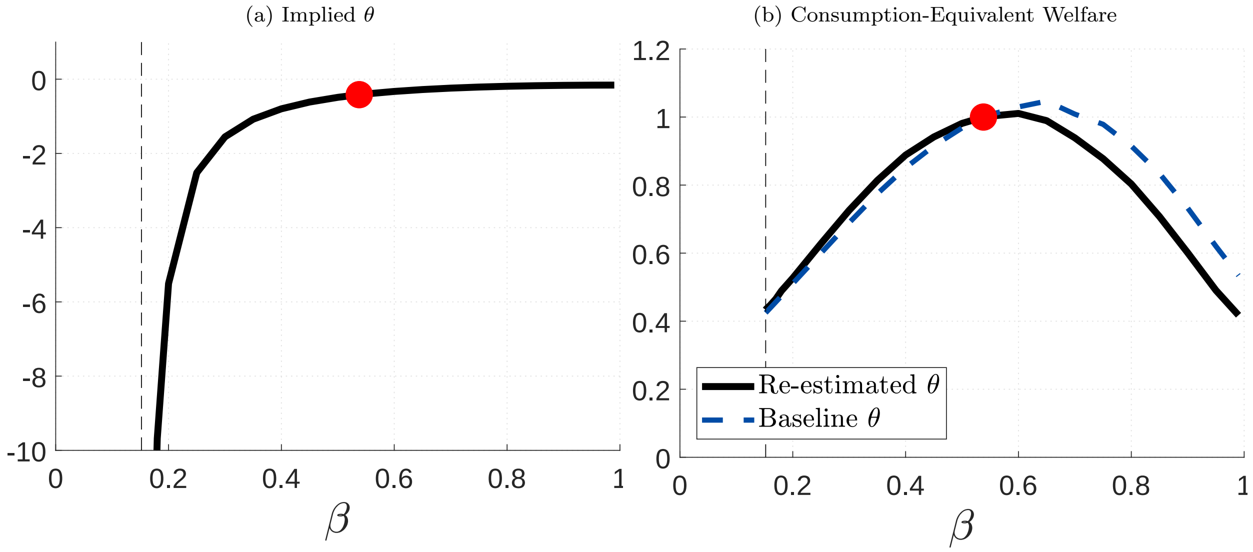


Figure notes: The left panel shows the implied θ required to estimate the same treatment effect observed in the data at the exogenously given β. The dashed vertical line the minimum value of β for which there exists a θ that can rationalize the observed average treatment effect. This is related to the discussion of Γ^{min} defined in Proposition 3. $\theta \to -\infty$ as β approaches this value from above. The right panel shows the implied consumption-equivalent welfare, normalized to one at our estimated parameters. Our estimated values are denoted by the circle in each graph.

The welfare implications are in Figure 8b. We focus first on the solid line. This is our baseline counterfactual in which θ is re-estimated to achieve the same average treatment effect. The differences here can be substantial. Increasing β from 0.25 to to our estimated value 0.538, for example, increases the consumption equivalent welfare gain by 59 percent. Perhaps more surprisingly, overestimating the intensive margin forces can similarly bias downward welfare gains. Assuming $\beta = 0.90$ instead of 0.538 lowers the implied welfare gains by 40 percent. We detail to the economic forces governing these trade-offs in the next section. For now, however, the results show that understanding effecient welfare gains depends critically on separately identifying the parameters governing the extensive (here, θ) and intensive (here, β) margins, as our procedure does.

D.1.1 Understanding Forces Behind This Pattern

To better understand the forces behind the pattern above, we also re-estimate the welfare gains while holding θ fixed at its baseline value. This is the dashed line in Figure 8b. The limited difference between the two lines shows that the welfare gains are primarily driven by the direct effect of β, and not the implied differences in θ.[31] Thus, understanding the main results above primarily requires understanding the impact of changing β. We study that here.

A useful starting point is to re-write total resources in the planner's allocation in terms of semi-elasticities. Recalling the aggregate production function defined in Proposition 8, we can then define the semi-elasticity of consumption with respect to the occupational cut-off, $\varepsilon_{c_p} := (\partial c_p / \partial \underline{z})/c_p$, as the sum of the aggregate input elasticities,

$$\varepsilon_{c_p} = \left(\frac{\eta}{1-\alpha}\right)\varepsilon_{N_s} + \left(\frac{1-\alpha-\eta}{1-\alpha}\right)\varepsilon_{Z}. \tag{D.6}$$

Equation (D.6) tells us the consumption change induced when the planner slightly shifts the occupational cut-off. There are two components to the consumption gains. The first is static – holding the ability distribution fixed, increasing the cut-off mechanically increases labor supply. This positively affects ε_{N_s} and negatively affects ε_Z. But key in this model is that shifting $\underline{z}$ also affects the ability distribution M through diffusion. This is the dynamic effect on production, as the mass of the population in each occupation changes as M changes.[32] Figure 9 plots the semi-elasticity ε_{c_p}, along with those of the two aggregate inputs defined in (D.6). They are evaluated at the baseline equilibrium cut-off.

The first thing to note about Figure 9a is that the elasticity is positive for any value of β. Thus, no matter the parameters, the planner can increase consumption by transition some baseline entrepreneurs to wage work. This is entirely a function of the diffusion externality. Moreover, as expected, it follows a similar shape to the overall welfare gains. Finally, Figure 9b shows that this is in large part driven by ε_Z. That is, the consumption response is primarily driven by the changes to ability in the economy.

Why, then, does ε_Z take this shape? This is at the heart of understanding how the overall welfare gains vary with the critical parameter β. Figure 10a provides a mechanical rationale: the numerator of ε_Z is approximately linear while the denominator is substantially more convex. But both of these curves have natural economic interpretations. The numerator, $\partial Z/\partial \underline{z}$, measures the change in economy-wide ability

[31] The difference between the two is driven by the fact that the welfare gains are declining in θ.

[32] It is straightforward to show that each of these semi-elasticities can be decomposed into a static and dynamic term, as $\varepsilon_j = \varepsilon_j^S + \varepsilon_j^D$ for $j = N_s, Z$. The static reallocation across occupations plays almost no quantitative role here. Thus, when interpreting the results here, one should think of them as driven by the dynamic diffusion effects.

Figure 9: The Semi-Elasticity of Consumption for the Social Planner

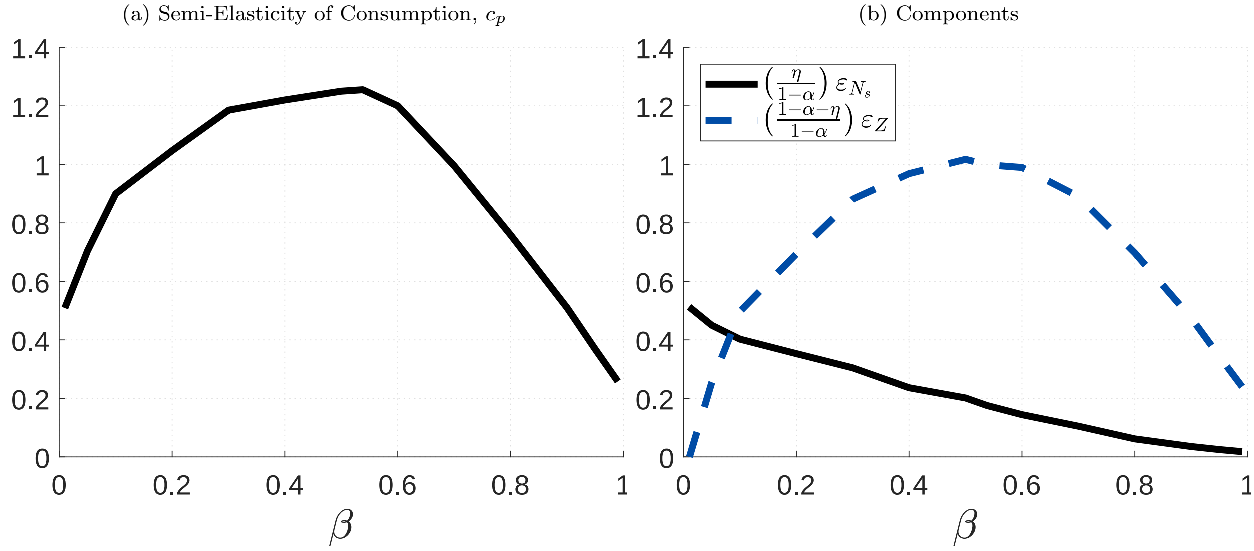


Figure notes: These semi-elasticities are evaluated at the baseline equilibrium cut-off $\underline{z}^*$ and equilibrium distribution $M^*(z;\underline{z}^*)$.

from a marginal increase in the cut-off. It is monotonically increasing – the higher β, the larger the potential impact on ability. This means that all else equal, a higher β induces a larger increase in consumption for the planner.

But the welfare *gains* depend on how that composite ability compares to the baseline equilibrium. This baseline ability is given by Z in Figure 10a, and also depends on β. In particular, higher β increases the gains from a good match. This increases ability and thus drives up the return to labor, which increases the wage. The higher wage induces more wage workers, as Proposition 1 shows that the baseline cut-off has the feature $\underline{z} \propto w^{\frac{1-\alpha}{1-\eta-\alpha}}$ (Figure 10b shows it graphically). These same steps are then compounded in equilibrium. With fewer, more able firms, diffusion accelerates even faster as agents further increase ability. The stationary equilibrium wage then takes the convex share of Figure 10a.

Together, these results highlight the two competing forces in the model, both of which can be seen in Figure 10. At low levels of β, the matching technology limits the aggregate welfare gains. At high levels of β, we see similar welfare gains, but for a different reason. Here, standard equilibrium forces already accomplish most of what the planner would want to accomplish. While the baseline economy is clearly richer, the returns to *additional* intervention by the planner at high β are low. We summarize these forces in Figure 10c, which plots average consumption across the baseline and efficient allocations. Consistent with these results, average baseline consumption grows more slowly than the efficient consumption at low β, then more quickly at high β.

Thus, these two competing economic forces – the race between technology and equilibrium prices in generating diffusion – are critical in generating the non-monotonicity observed in the headline results. Moreover, they are governed are the diffusion parameters we estimate. Thus, estimating these parameters plays an important role in understanding the aggregate implications in the economy.

Much like our main results, the planner's problem shows that separating the extensive and intensive margin is critical to understanding the gains from policy, whether they be a change to the matching technology (as in the main text) or the fully efficient planner's allocation (here).

Figure 10: Equilibrium Forces and the Pattern of ε_Z

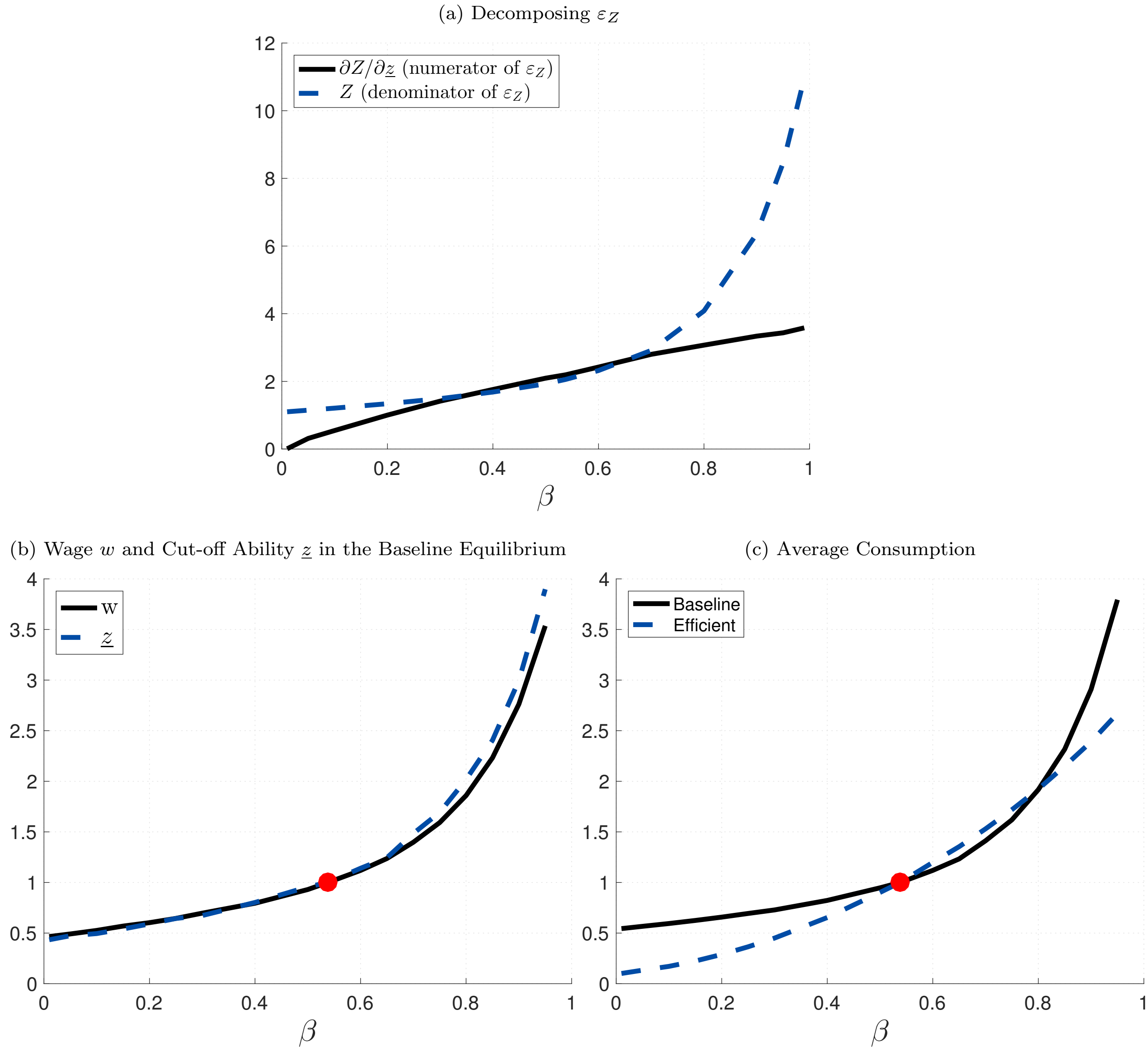


Figure notes: In Figures 10b and 10c, our estimated values are denoted by the circle in each graph and normalized to one.

E Quantitative Implications of Mismeasurement

We explore the quantitative consequences of mis-measuring profit here. We make the following assumption: for all individuals, we observe $\pi = \tau\pi^*$, where $\tau \sim N(0, \sigma_\tau)$ is classical measurement error (in logs), π is observed profit, and π^* is true profit. We assume that $\tau \sim N(0, \sigma_\tau)$, where σ_τ is known but the individual realizations are not. As discussed in Appendix C this can be extended to estimate the distribution of τ. We leave this aside for simplicity here. Define the function

$$g(\pi^*, \hat{\pi}^*; \mathbf{\Gamma}) = c + \rho \log(\pi^*) + \beta \log\left(\max\left\{1, \frac{\hat{\pi}^*}{\pi^*}\right\}\right)$$

where $\mathbf{\Gamma} := (c, \rho, \beta)$ is the parameter set. Our first stage regression is $\log(\pi'^*) = g(\pi^*, \hat{\pi}^*; \mathbf{\Gamma})$, but is complicated by the mis-measured profit on the right hand side of this equation. Here, we re-estimate this regression with mis-measured profit and show how the results change.

E.1 Estimation Procedure

Some notation is required. For any variable x, define $\tilde{x} = \log(x)$, $f_x(x)$ as the probability density function, and $\phi_x(t) = \int_{\mathbb{R}} e^{itx} f_x(x)dx$ as its characteristic function.

We first estimate the characteristic functions of the observed π and $\hat{\pi}$,

$$\begin{aligned} \hat{\phi}_{\tilde{\pi}}(t) &= \left(\frac{1}{n}\sum_{j=1}^{n} e^{it\log(\pi_j)}\right)\phi_{k,\pi}(h_\pi t) \\ \hat{\phi}_{\tilde{\hat{\pi}}}(t) &= \left(\frac{1}{n}\sum_{j=1}^{n} e^{it\log(\hat{\pi}_j)}\right)\phi_{k,\hat{\pi}}(h_{\hat{\pi}} t) \end{aligned}$$

The first term in parenthesis is the empirical characteristic function using mis-mesaured variables $(\pi_j, \hat{\pi}_j)$. The latter term, $\phi_k(ht)$, is the Fourier transform of a kernel density estimator with bandwidth h.[33]

Since $\phi_{\tilde{\pi}^*}(t) = \hat{\phi}_{\tilde{\pi}}(t)/\phi_{\tilde{\tau}}(t)$ and similarly for $\hat{\pi}$ (due to the independence of π and

[33] A well-known issue with this type of estimation is the inaccuracy of the empirical characteristic function in the tails of the distribution. A kernel density estimate is one version of what is generally referred to as a dampening factor to improve accuracy. The fact that ϕ_k enters multiplicatively follows because a kernel estimator is also a type of convolution.

$\hat{\pi}$), we recover the estimated densities of π and $\hat{\pi}$ from an inverse Fourier transform,

$$\begin{aligned} f_{\pi^*}(\pi^*) &= \frac{1}{2\pi}\int \hat{\phi}_{\pi^*}(t)e^{-it\pi^*}dt \\ f_{\hat{\pi}^*}(\hat{\pi}^*) &= \frac{1}{2\pi}\int \hat{\phi}_{\hat{\pi}^*}(t)e^{-it\hat{\pi}^*}dt \end{aligned}$$

where π in the ratio $1/(2\pi)$ should be understood to be $\pi \approx 3.14$ instead of profit (as to not introduce any additional notation).

With the true distribution functions, we can estimate our regression in any number of ways. We use the minimum distance estimator proposed by Hsiao (1989). That is, we choose parameters $\mathbf{\Gamma} := (\tilde{c}, \rho, \beta)$ to solve

$$\min_{\mathbf{\Gamma}} \sum_{i=1}^{n} \left(\pi_i' - G(\pi_i, \hat{\pi}_i; \mathbf{\Gamma})\right)^2 \tag{E.1}$$

where

$$G(\pi, \hat{\pi}; \mathbf{\Gamma}) = \int\int g(\pi^*, \hat{\pi}^*) f_{\pi^*|\pi}(\pi^*|\pi, \mathbf{\Gamma}) f_{\hat{\pi}^*|\hat{\pi}}(\hat{\pi}^*|\hat{\pi}, \mathbf{\Gamma}) d\pi^* d\hat{\pi}^*$$

The minimum distance estimator in (E.1) is also extended to unknown error distributions by Li (2002) using the repeated-measurement framework discussed in Appendix C.

E.2 Updated Calibration

After estimating the diffusion parameters, we update the calibration to take these values into account. The updated parameters are listed in Table 8, along with the baseline for comparison. We do so in two scenarios: $\sigma_\tau = 0.30$ and $\sigma_\tau = 1$.

E.3 Quantitative Exercise

We now study the gains from the same exercise as in the text. The main results are in Table 9. The first column fixes the wage at its baseline level, isolating the impact of the changing ability distribution. The second column allows the wage to adjust, adding in the additional general equilibrium effect on prices.

Overall, by biasing our parameter β toward zero, our results are a lower bound on the gains at-scale. Figure 11 shows that the same results on the many-to-one relationship between the ATE and at-scale gains holds.

Table 8: Updated Parameter Values

Model Parameter	Description	Parameter (Baseline)	Parameter ($\sigma_\tau = 0.3$)	Parameter ($\sigma_\tau = 1$)
Exogenously varied:				
σ_τ	St. dev. of distortions	0	0.3	1.0
Group 1				
β	Intensity of diffusion	0.538	0.629	0.883
ρ	Persistence of ability	0.595	0.371	0.494
θ	Match technology "quality"	-0.417	-0.326	-0.179
Group 2				
δ	Death rate of firms	0.016	0.016	0.016
σ_0	St. dev. of new entrant ability distribution	0.961	0.961	0.961
ν	Firm bargaining weight	0.5	0.5	0.5
Group 3				
σ	St. dev. of exogenous ability shock distribution	0.75	0.74	0.66
c	Growth factor in ability evolution	-1.92	-2.23	-2.41
ω	Consumption utility weight	0.53	0.54	0.62
α	Ability elasticity in supplier search	0.36	0.36	0.36
η	Ability elasticity in supplier search	0.05	0.05	0.05

Table notes: Group 1 is jointly chosen from the experimental data. Parameters in Group 2 are calibrated to jointly match moments. Group 3 are also set to match baseline data moments, but match 1-1 with target moments. Both are set to match the same set of moments discussed in the main text (see Table 2 for details).

Table 9: Equilibrium Moments

	$\sigma_\tau = 0.3$		$\sigma_\tau = 1$	
	(1)	(2)	(3)	(4)
	Fixed Wage	At-Scale	Fixed Wage	At-Scale
Income	1.08	1.12	1.20	1.38
Ability	1.08	1.14	1.20	1.42
Aggregate Labor Supply	0.92	0.99	0.89	1.00
Wage	1.00	1.14	1.00	1.39

Table notes: All are measured relative to the baseline equilibrium at the give value of σ_τ. Each column reports the new stationary equilibrium after shocking the matching technology, where the first (columns 1 and 3) holds the wage fixed at its baseline level and the second allows it to adjust.

Figure 11: Range of Aggregate Gains for each ATE

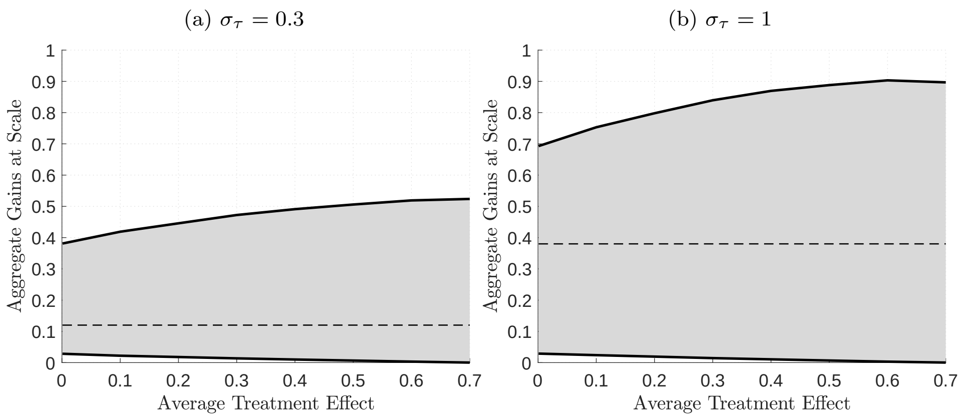


Figure notes: Shaded area is all possible aggregate gains for $(\beta, \rho) \in [0.20, 0.95] \times [0.20, 0.95]$, where θ is chosen to match the ATE on the horizontal axis. The baseline estimate is given by the dashed line.

F Implementing the Same Procedure in the RCT of Cai and Szeidl (2018)

F.1 RCT Details

In an innovative recent paper, Cai and Szeidl (2018) (CS hereafter) conduct an RCT among 2,820 Chinese firms. Treated firms (1,500 of 2,820) are randomly placed into a group of approximately 10 other firms, then compared to a control group with no prearranged meetings.

While similar in style to the RCT used in the main body of the paper, there are a number of differences. First, these are group meetings instead of individual meetings. Second, the meetings are substantially more intense: firms are expected to meet monthly for a year.[34] Third, these firms are larger. At baseline the average firm has 35 workers. Finally, they cross-randomize information about new financial products to track the diffusion of information directly.

Firms are surveyed 3 times: before the treatment, 1 year post-treatment (i.e., at the end of the treatment period), and 2 years post-treatment. We refer to these as $t = 0, 1, 2$. We estimate our procedure off the $t = 1$ data and later ask whether we can match the effect at $t = 2$.

F.2 Overview of Empirical Results

While we will not do justice to the full set of results provided in CS, we provide a brief overview here to relate them back to our baseline RCT in the main text and provide context for modeling decisions. Like our baseline results, CS find important effects on firm performance. In a regression of the form

$$y_{it} = \lambda_0 + \overbrace{\lambda_1 \cdot \mathbb{1}_{t=1} + \lambda_2 \cdot \mathbb{1}_{t=2}}^{\equiv \text{ time effects}} + \overbrace{\lambda_3 \cdot (\mathbb{1}_{t=1} \times T_{it}) + \lambda_4 \cdot (\mathbb{1}_{t=2} \times T_{it})}^{\equiv \text{ per-period ATE}} + FirmFE_i + \varepsilon_{it}$$

they find positive and statistically significant effects at $t = 1$ (i.e., $\lambda_3 > 0$) for sales, profit, employment, and productivity. These meetings do indeed seem to leave firms better off. Unlike our baseline RCT, however, these effects persist at $t = 2$, a full year after the treatment concludes (i.e. $\lambda_4 > 0$).[35]

[34] Take-up is still high, with average attendance of 87 percent.

[35] Productivity here is measured as firm-level TFP from estimating a revenue production function among control firms. This is the only outcome of those listed in which the point estimate at $t = 2$ is statistically insignificant, but it

A number of additional results provide context for these firm performance effects. First, they find persistent changes in management practices.[36] Thus, direct components of firm-level productivity increase. Second, they cross-randomize information on a new financial product to test whether information is indeed flowing between firms within the group, and find that it does. We (and CS) take this as a direct measure that information is flowing between firms in the group.

Finally, CS provide one measure of group-level heterogeneity, asking whether treated firms who have larger average group members enjoy a larger treatment effect. Denoting $\overline{n}_i^m$ as the average firm size of firm i's matches, they run

$$y_{it} = \lambda_0 + \lambda_1 \log(\overline{n}_i^m) + \varepsilon_{it} \quad \text{for } i \text{ in the treatment group.} \tag{F.1}$$

They find statistically significant increases in sales and profit. CS use (F.1) as an "internal consistency check," in the sense that most reasonable theories would predict $\lambda_1 > 0$. As is hopefully clear at this point, this type of regression has an additional role: it is a critical test for extrapolating these results to at-scale implications. We will exploit this regression below in our estimation.

F.3 Model

The empirical setting and results motivate our model structure. Because these are larger firms, we we study this RCT in the context of a more classic Hopenhayn (1992) style model. Given the results on productivity and management practices, we allow diffusion of firm productivity directly, instead of the ability to seek out suppliers. This assumption is more in line with the existing growth literature (Lucas, 2009; Perla and Tonetti, 2014, and many others). Finally, we construct our learning process to conform to the available empirical results, which we discuss more below.

Basics: Production and Households The model period is one year (the length of the exogenous matches in the RCT). There is a measure one of firms, each of which produces according to the production function $y_t = z_t^{1-\alpha-\eta} n_t^\alpha k_t^\eta$, where z_t is firm-level productivity, n_t is labor, and k_t is capital. Capital and labor are traded on a competitive spot markets with prices r_t and w_t. Each period δ firms exit and are

is still positive. We read less into this result, as it is likely the most noisily estimated.

[36]These include an overall management index, along with components on the evaluation and communication of employee performance, the setting of targets, process documentation, and delegation of power.

replaced by δ new firms, who draw initial productivity from $z \sim G(z)$.[37] As in the main text, firms draw idiosyncratic shocks $\varepsilon \sim F$ and imitation shocks $\hat{z} \sim \widehat{M}$.

A representative household with flow utility $u(C_t)$ provides labor and capital, and owns all firms. Its utility is given by:

$$\begin{aligned} \max_{\{C_t, K_{t+1}\} \geq 0} \quad & \sum_{t=0}^{\infty} (1-\delta)^t u(C_t) \\ s.t. \quad & C_t + K_{t+1} - (1-\lambda)K_t = w_t + r_t K_t + \Pi_t \\ & K_0 \text{ given} \end{aligned}$$

where Π_t is the aggregate profits from all operating firms and λ is depreciation rate of capital. We assume the household discounts at the firm exit rate for simplicity.

The aggregate state of the economy is the distribution of firm-level productivity, $M(z)$, and the aggregate capital stock, K.

Learning and Diffusion Given the high cost-effectiveness of the program, CS posit a number of possibilities for why firms did not self-organize these meetings. These include search costs, trust barriers and lack of familiarity with other managers, and a free-rider problem in which managers expect others to pay the cost of organization. Motivated by these "missing" meetings, we set up a source distribution in which a firm receives no meetings with probability $1-\theta$. With probability θ, the firm joins a group of exogenous size N. These N firms are uniformly random draws from the equilibrium productivity distribution M. We denote $\hat{z}_1, \ldots, \hat{z}_N$ to be the productivities of the N matched firms.

We next define a match $\hat{z}$ in this context, which in general can take any function over the characteristics of these N firms. Here we are constrained by the results reported in CS, who report how the treatment effect varies by only the average size of the N firms. As such, we assume that $\hat{z} = \sum_{i=1}^{N} \hat{z}_i / N$ so that we can use their provided moment. If a firm does not receive a match, it gets $\hat{z} = 0$.[38] We can therefore write

[37] In the more classic Hopenhayn (1992) or Melitz (2003) sense, the model can be easily extended to include endogenous firm entry/exit by introducing fixed costs, as opposed to our assumed exogenous entry/exit margin. Adding this additional margin does not change the results we focus on here and we therefore exclude it for simplicity. This assumption also does not affect identification. Our procedure relies only on firms in operation at a given point in time, so that the details of past entry are immaterial.

[38] This is of course not a critique of the extremely useful publicly-provided dataset of CS. We note this only to highlight that there is no theoretical benefit to making this assumption, and we do so because it is the only estimating moment of group-level heterogeneity available in their public data.

the source distribution as

$$\widehat{M}(\hat{z}) = 1 - \theta + \theta Q(\hat{z}),$$

where $Q(\cdot)$ is the N-draw sampling distribution of the mean derived from the equilibrium productivity distribution M.

Finally, we note that within treated firms, there is no differential effect between firms with $\hat{z} > z$ or $\hat{z} < z$. Therefore, we remove the max operator and assume that the law of motion takes the form

$$z_{t+1} = e^{c+\varepsilon_t} z_t^{\rho} \left(1 + \frac{\hat{z}_t}{z_t}\right)^{\beta}. \tag{F.2}$$

Equation (F.2) shows that if the firm does not interact that period ($Pr = 1-\theta$), it gains nothing from its $\hat{z}_t = 0$ draw. Conditional on meeting ($Pr = \theta$), however, there will be gains from doing so. Those gains are increasing in the average productivity of matched firms.

Taken together, the firm's problem can be written as (with the aggregate state suppressed, as we will focus on a stationary equilibrium):

$$\begin{aligned} v(z) &= \max_{n,k \geq 0} \; z^{1-\alpha-\eta} n^{\alpha} k^{\eta} - wn - rk + (1-\delta) \int_{\varepsilon} \int_{\hat{z}} v(z'(\hat{z}, \varepsilon; z)) \widehat{M}(d\hat{z}, M) dF(\varepsilon) \\ s.t. &\qquad z'(\hat{z}, \varepsilon; z) = e^{c+\varepsilon} z^{\rho} \left(1 + \frac{\hat{z}_t}{z_t}\right)^{\beta} \end{aligned}$$

Equilibrium The stationary equilibrium of this economy is an invariant distribution $M^*(z)$, household decision rules C, K', firm decision rules n, k, and value function v such that the household's and firms' value function solves their respective problems with the associated decision rules, markets clear

1. `labor market:` $\int_z n(z) dM^*(z) = 1$
2. `capital market:` $\int_z k(z) dM^*(z) = K$
3. `consumption market:` $\int_z z^{1-\alpha-\eta} n^{\alpha} k^{\eta} dM^*(z) = C + \lambda K$

and the relevant aggregates are consistent

1. `profit:` $\int_z \pi(z) dM^*(z) = \Pi$

2. `law of motion for ability:`

$$
\begin{aligned}
M' &:= \Lambda(M(z')) \\
&= \delta G(z') + (1-\delta)\int_0^\infty \int_0^\infty F(\log(z') - \rho\log(z) + \beta\log(1+\hat{z}/z) - c)d\widehat{M}(\hat{z})dM(z)
\end{aligned}
$$

with $M^*(z) = \Lambda(M^*(z))$.

F.4 Estimating Diffusion Parameters

We begin by using our two-step procedure to estimate the key diffusion parameters (β, ρ, θ).

The production function here generates the usual Cobb-Douglas result that inputs labor and capital, sales, and profit are all proportional to z. Therefore, we are free to use any of these moments for identification (see also Appendix Section C.2 for a further generalization).

Averages are also proportional to z. If a firm matches with N firms of size $\hat{n}_1, \ldots, \hat{n}_N$, then we can infer the average productivity as

$$
\hat{n} := \frac{\sum_{j=1}^N \hat{n}_j}{N} = \left(\frac{\alpha}{w}\right)^{\frac{1-\eta}{1-\alpha-\eta}} \left(\frac{\eta}{r}\right)^{\frac{\eta}{1-\alpha-\eta}} \frac{\sum_{j=1}^N \hat{z}_j}{N} \propto \hat{z}. \tag{F.3}
$$

Given these results, we focus on firm size here for our estimation. As discussed above, it is the only moment available in the public CS data for the first step of our estimation procedure. Rather than introduce a second dependent variable, we use firm size in the second step as well.

Following our procedure in the text, we will estimate the diffusion parameters using only $t = 0, 1$ data then later check whether the time series matches $t = 2$ outcomes. Thus, the first step of our procedure is to estimate

$$
\log(n_i') = c + \rho\log(n_i) + \beta\log\left(1 + \frac{\hat{n}_i}{n_i}\right) + \varepsilon \quad \text{for all } i \text{ in treatment} \tag{F.4}
$$

where $\hat{n}_i$ is the average size of matched firms as defined in (F.3). Given $(\hat{\rho}, \hat{\beta})$ we then estimate θ with the same procedure as the main text.

$$
\min_\theta \quad abs\left(\frac{\mathbb{E}[n_T']}{\mathbb{E}[n_C']} - \frac{\int\int \pi^\rho \left(1+\hat{n}/n\right)^\beta d\widehat{H}_T(\hat{n})dH_T(n)}{\int\int n^\rho \left(1+\hat{n}/n\right)^\beta d\widehat{M}(\hat{n};\theta)dH_C(n)}\right) \tag{F.5}
$$

where H_C, H_T are the empirical baseline distributions of control and treatment firms, $\widehat{M}$ is the source distribution for control firms, and $\widehat{H}_T$ is the source distribution for treated firms (given exogenously by the empirical implementation). We measure the empirical ratio in (F.5) as the average treatment effect

$$\log(n_i') = \lambda_0 + \lambda_1 T_i + Controls_i + \nu_i \tag{F.6}$$

where $T_i = 1$ if i is in the treatment group. Table 10 provides the regression estimates for (F.4) and (F.6).

Table 10: Identification Moments

	(1)	(2)
β	0.276	
	(0.053)***	
ρ	0.955	
	(0.028)***	
Treatment		0.076
		(0.044)*
R^2	0.764	0.395
Baseline Control Avg	–	2.694

Table notes: Standard errors are in parentheses. Statistical significance at 0.10, 0.05, and 0.01 is denoted by *, **, and, ***.

Column (1) show that the average firm size is indeed a good predictor of treatment effect magnitude. The ATE in column (2) then implies $\theta = 0.199$. That is, the model infers that it is quite unlikely that such a CS-style group would be created without the intervention.

F.5 Remaining Calibration

We calibrate the remaining model to target parameters similar to the main text, using CS data and other relevant moments. We choose 5 parameters that match directly to their moments. These include a 9 percent firm death rate ($\delta = 0.09$) to match exit rates in China (e.g. Lu, 2021). The standard deviation of new entrant ability matches the standard deviation of log profit for firms that have been open for less than 1 year, which implies $\sigma_0 = 1.23$. The depreciation rate is set to a standard value of $\lambda = 0.06$. Finally, we have the Cobb-Douglas exponents on capital η and labor α. We set $\eta = 0.20$ to match the median firm's baseline capital-output ratio $(rk)/y = 0.20$ then set α to match the median firm's profit-sales ratio, $\pi/y = 0.12$. This implies $\alpha = 0.68$. Finally, we set the standard deviation of the exogenous ability shock to $\sigma = 0.45$ and the productivity drift $c = -1.11$. These two parameters jointly match the standard deviation of log profit in the economy and the ratio of average profit of all firms relative to those with less than 1 year of operation. Parameters and moments are in Table 11.

Table 11: Targets and Parameter Choices

Model Parameter	Description	Parameter Value	Target Moment	Source	Target Value	Model Value
Group 1	*From RCT*					
β	Intensity of diffusion	0.276	Estimated parameter from regression	RCT results	0.276	0.276
ρ	Persistence of ability	0.955	Estimated parameter from regression	RCT results	0.955	0.955
θ	Match technology "quality"	0.199	Treatment effect at $t = 1$	RCT results	0.076	0.076
Group 2	*Matched one-to-one with parameter*					
δ	Death rate of firms	0.09	Average exit rate in China	Literature (Lu, 2021)	34	34
σ_0	St. dev. of new entrant ability distribution	1.23	Variance of log profit among new entrants	CS Baseline	1.23	1.23
α	Cobb-Douglas share, n	0.68	Median firm π/y	CS Baseline	0.12	0.12
η	Cobb-Douglas share, k	0.20	Median firm $(rk)/y$	CS Baseline	0.20	0.20
λ	Depreciation rate	0.06	Literature	–	–	–
Group 3	*Jointly targeted*					
σ	St. dev. of exogenous ability shock distribution	0.45	Standard deviation of log profit in all firms	CS Baseline	1.34	1.34
c	Growth factor in ability evolution	-1.11	Ratio of average profit of all firms to new entrants	CS Baseline	1.12	1.12

Table notes: Group 1 is jointly chosen from the experimental data. Group 2 are also set to match baseline data moments, but match 1-1 with target moments. Parameters in Group 3 are calibrated to jointly match moments.

F.6 Treatment Effect Persistence

In the main text, we showed that the treatment effect persistence is decreasing in β. In our baseline Kenyan RCT we estimate $(\beta, \rho) = (0.538, 0.595)$. Here, we estimate $(0.276, 0.955)$. Our estimates of both β and ρ predict more persistent treatment effects than our baseline model.

We compare this to the empirics in Figure 12. We plot 3 time paths: the empirical treatment effect (which is available for 2 years post-treatment), the estimated model effect, and the estimated model effect when we assume our Kenyan RCT values for β and ρ. We extend the latter two series for 5 years to trace the dynamics over a longer horizon.

Figure 12: Dynamics of Average Treatment Effect (Firm Size)

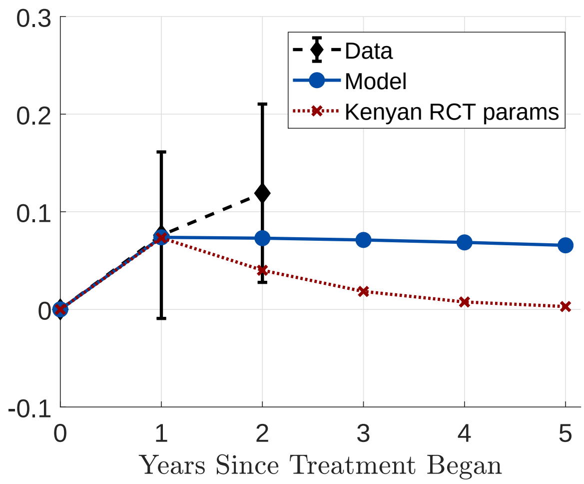


Figure notes: Dashed line is the data with 95 percent confidence interval, for which data is available at $t = 0, 1, 2$. Solid line is the estimated model $(\beta, \rho, \theta) = (0.276, 0.955, 0.199)$. For comparison, we include the results at our Kenyan RCT values of β and ρ, re-estimating θ to hit the $t = 1$ ATE, which implies $(\beta, \rho, \theta) = (0.538, 0.595, 0.496)$. We extend the model-derived RCT for 5 post-treatment years to study fade-out.

The model is consistent with the persistent gains.[39] Even 5 years post-treatment, the model predicts that 89 percent of the initial benefits remain. In comparison, if we replace β and ρ by our estimated values in Kenya, the fade-out is more substantial and nearly complete by $t = 4$. The results highlight the importance of estimating these parameters in governing the time series of the treatment effect.

[39] The slight increase observed in the treatment effect from $t = 1$ to $t = 2$ is statistically insignificant by any reasonable cutoff.

F.7 Quantitative Gains at Scale

We conduct the same exercises as the main text. To measure the aggregate implications, we permanently shock the matching technology to increase average match quality, in line with the extensive margin focus of the RCT results. We do so by shocking the parameter θ so that it is 25 percent closer to its limit of $\theta = 1$. We study the new stationary equilibrium and compare it to the baseline equilibrium. Aggregate moments are reported in Table 12. We present two steady states, both of which operate under the new matching function. The first (in column 2) fixes the wage at its baseline level. The second (in column 3) allows the wage to adjust as well.

Table 12: Equilibrium Moments

	(1) Baseline	(2) Fixed Wage	(3) At-Scale
Income	1.00	1.13	1.05
Ability	1.00	1.39	1.39
Aggregate Labor Supply	1.00	1.00	1.00
Wage	1.00	1.00	1.05

Table notes: Column (1) is the initial equilibrium, normalized to one. (2) and (3) report the new stationary equilibrium after shocking the matching technology, where (2) holds the wage fixed at its baseline level and (3) allows it to adjust.

The direct effect of making it easier to learn from high ability agents is that average ability rises by 39 percent and income by 13 percent. Some of that is eliminated by the higher general equilibrium wage, with the net effect of a 5 percent increase in total household income.

We next ask the importance of measuring treatment effect heterogeneity, as in the main text. We vary $(\beta, \rho) \in [0.20, 0.95] \times [0.20, 0.95]$. For each, we continually update θ to match a given average treatment effect. We vary the ATE from 0 to 18 percent, which traces out the range of possible aggregate outcomes by ATE.[40] Those results are in Figure 13. Similar results emerge as in the main text – the set of possible aggregate outcomes for a given treatment effect can be large.

[40] The set of feasible ATEs for the range of (β, ρ) we consider is smaller here than in the main text, as our diffusion process requires $\theta \in [0, 1]$. See the discussion surrounding Proposition 3 for more details on this constraint.

Figure 13: Range of Aggregate Gains for each ATE (Firm Size)

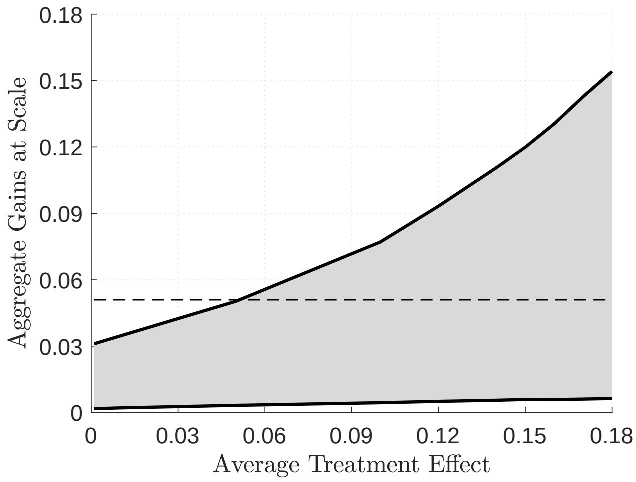


Figure notes: Shaded area is all possible aggregate gains for $(\beta, \rho) \in [0.20, 0.95] \times [0.20, 0.95]$, where θ is chosen to match the ATE on the horizontal axis. The baseline estimate at $(\beta, \rho) = (0.276, 0.955)$ is given by the dashed line.

G Proofs

G.1 Proof of Proposition 1

We begin by detailing the underlying arithmetic of the model, then use those results to prove Proposition 1 at the end of this section.

Solving the Bargaining Problem as a Function of Supplier Marginal Cost m Solving the optimal input choices for the firm implies profit is

$$\pi^f(c,w) = \left(\frac{\alpha}{p_x}\right)^{\frac{\alpha}{1-\eta-\alpha}} \left(\frac{\eta}{w}\right)^{\frac{\eta}{1-\eta-\alpha}} (1-\alpha-\eta). \tag{G.1}$$

A supplier has profit function $\pi^s = (p_x - m)x$ where m is its given marginal cost. Given that they take as given the firm's decision on inputs, this implies we can write this profit as

$$\pi^s(p_x,m) = \left(\frac{\alpha}{p_x}\right)^{\frac{1-\eta}{1-\eta-\alpha}} \left(\frac{\eta}{w}\right)^{\frac{\eta}{1-\eta-\alpha}} (p_x - m).$$

Re-writing the bargaining problem $\pi(p_x)^\nu \pi^s(p_x,m)^{1-\nu}$ taking these derivations into account yields

$$\max_{p_x} \quad \left(\frac{\eta}{w}\right)^{\frac{\eta}{1-\eta-\alpha}} (1-\alpha-\eta)^\nu \alpha^{\frac{1-\eta-\nu(1-\eta-\alpha)}{1-\eta-\alpha}} c^{\frac{\nu(1-\eta-\alpha)+\eta-1}{1-\eta-\alpha}} (p_x - m)^{1-\nu}$$

Log differentiating gives the solution

$$p_x = \left(\frac{1-\eta-\nu(1-\eta-\alpha)}{\alpha}\right) m \tag{G.2}$$

Replacing p_x in the firm's profit function (G.1) with the value from (G.2) yields

$$\pi = \left(\frac{\alpha}{1-\eta-\nu(1-\eta-\alpha)}\right)^{\frac{\alpha}{1-\eta-\alpha}} (1-\eta-\alpha)\alpha^{\frac{\alpha}{1-\eta-\alpha}} \left(\frac{\eta}{w}\right)^{\frac{\eta}{1-\eta-\alpha}} m^{\frac{-\alpha}{1-\eta-\alpha}} \tag{G.3}$$

Optimal Search Intensity Now that we have profit as a function of the supplier's marginal cost m in (G.3), we need to solve for search intensity s. Recall that $m = exp(-s)z^{\frac{\alpha+\eta-1}{\alpha}}$. Plugging this into (G.3),

$$\pi^f(m) = \left(\frac{\alpha}{1-\eta-\nu(1-\eta-\alpha)}\right)^{\frac{\alpha}{1-\eta-\alpha}} (1-\eta-\alpha)\alpha^{\frac{\alpha}{1-\eta-\alpha}} \left(\frac{\eta}{w}\right)^{\frac{\eta}{1-\eta-\alpha}} exp(-s)^{\frac{-\alpha}{1-\eta-\alpha}} z$$

The relevant part of the firm's utility function for this problem is the static utility flow $\omega \log(\pi) + (1-\omega)\log(1-s)$. Plugging in π and solving for s yields

$$s = 1 - \left(\frac{1-\omega}{\omega}\right)\left(\frac{1-\eta-\alpha}{\alpha}\right) \tag{G.4}$$

Occupational Choice Given the decision rules derived above, the model therefore has a cutoff rule for occupational choice. To see this, note that because the continuation values between workers and entrepreneurs are identical, we can focus on the flow utility payoff. After a bit of algebra, these are

$$u^f(w) = \omega \log(C_1) + (1-\omega)\log(1-s) - \frac{\eta\omega}{1-\eta-\alpha}\log(w) + \omega \log(z)$$

with constants

$$\begin{aligned} C_1 &= \left(\frac{\alpha}{1-\eta-\nu(1-\eta-\alpha)}\right)^{\frac{\alpha}{1-\eta-\alpha}} (1-\eta-\alpha)\alpha^{\frac{\alpha}{1-\eta-\alpha}}\eta^{\frac{\eta}{1-\eta-\alpha}} exp\left(\left(\frac{1-\omega}{\omega}\right)\left(\frac{1-\eta-\alpha}{\alpha}\right)-1\right)^{\frac{-\alpha}{1-\eta-\alpha}} \\ s &= 1 - \left(\frac{1-\omega}{\omega}\right)\left(\frac{1-\eta-\alpha}{\alpha}\right) \end{aligned}$$

More simply for workers, flow utility is $u^w(w) = \omega \log(w)$. Firm operation is preferred when $u^f(w) \geq u^w(w)$, which implies a cut-off $\underline{z}$

$$\underline{z} = w^{\frac{1-\alpha}{1-\eta-\alpha}} \exp\left(-\log(C_1) - \frac{1-\omega}{\omega}\log\left[\left(\frac{1-\omega}{\omega}\right)\left(\frac{1-\eta-\alpha}{\alpha}\right)\right]\right)$$

Thus, the cutoff has the feature that $\log(\underline{z}) \propto \log(w)$, where w is the equilibrium wage.

Proof of Proposition 1 With these results, Proposition 1 follows quickly.

Proof. Plugging (G.4) into the profit function yields

$$\begin{aligned} \pi &= \left(\frac{\alpha}{1-\eta-\nu(1-\eta-\alpha)}\right)^{\frac{\alpha}{1-\eta-\alpha}} (1-\eta-\alpha)\alpha^{\frac{\alpha}{1-\eta-\alpha}} \left(\frac{\eta}{w}\right)^{\frac{\eta}{1-\eta-\alpha}} \\ &\quad \times \; exp\left(\left(\frac{1-\omega}{\omega}\right)\left(\frac{1-\eta-\alpha}{\alpha}\right)-1\right)^{\frac{-\alpha}{1-\eta-\alpha}} z. \end{aligned}$$

Thus, we have $\pi = A(w)z$ in equilibrium, where A depends on parameters and the equilibrium wage w. Replacing $m = exp(-s)z^{\frac{\alpha+\eta-1}{\alpha}}$ in the equilibrium input price function (G.2) gives

$$p_x = \left(\frac{1-\eta-\nu(1-\eta-\alpha)}{\alpha}\right) exp\left(\left(\frac{1-\omega}{\omega}\right)\left(\frac{1-\eta-\alpha}{\alpha}\right)-1\right) z^{\frac{\alpha+\eta-1}{\alpha}}$$

as required. ■

G.2 Proof of Proposition 2

Proof. This result is a special case of Proposition 3. ■

G.3 Proof of Proposition 3

The bounds used in Proposition 3 are given by

$$\begin{aligned}
\Gamma^{min} &= \inf_{\theta} \frac{\int\int \pi^{\rho} \max\{1,\hat{\pi}/\pi\}^{\beta} d\widehat{H}_{T,\pi}(\hat{\pi}) dH_{T,\pi}(\pi)}{\int\int \pi^{\rho} \max\{1,\hat{\pi}/\pi\}^{\beta} d\widehat{M_{\pi}}(\hat{\pi};\pi,\theta) dH_{C,\pi}(\pi)} \\
\Gamma^{max} &= \sup_{\theta} \frac{\int\int \pi^{\rho} \max\{1,\hat{\pi}/\pi\}^{\beta} d\widehat{H}_{T,\pi}(\hat{\pi}) dH_{T,\pi}(\pi)}{\int\int \pi^{\rho} \max\{1,\hat{\pi}/\pi\}^{\beta} d\widehat{M_{\pi}}(\hat{\pi};\pi,\theta) dH_{C,\pi}(\pi)}.
\end{aligned}$$

We proceed with the proof under those bounds.

Proof. In the model, we can write $\pi' = g(z,\hat{z},\varepsilon) = Ae^{c+\varepsilon} z^{\rho} \max\{1,\hat{z}/z\}^{\beta}$ by Assumptions 1 and 2 for some constant A. Since g is continuous, for a density $f(z,\hat{z},\varepsilon)$ we have

$$\mathbb{E}[\pi'] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(z,\hat{z},\varepsilon) f(z,\hat{z},\varepsilon) d\hat{z} dz d\varepsilon$$

This follows from what is sometimes referred to as the "law of the unconscious statistician."[41] Inserting the correct joint distributions implies

$$\frac{\mathbb{E}_T[\pi']}{\mathbb{E}_C[\pi']} = \frac{\int\int\int z^{\rho} \max\{1,\hat{z}/z\}^{\beta} d\widehat{H}_T(\hat{z}) dH_T(z) dF_T(\varepsilon)}{\int\int\int z^{\rho} \max\{1,\hat{z}/z\}^{\beta} d\widehat{M}(\hat{z};z,\theta) dH_C(z) dF_C(\varepsilon)}.$$

Applying the proportionality assumption in Assumption 2 and the orthogonaility condition of Assumption 1 gives us

$$\frac{\mathbb{E}_T[\pi']}{\mathbb{E}_C[\pi']} = \frac{\int\int \pi^{\rho} \max\{1,\hat{\pi}/\pi\}^{\beta} d\widehat{H}_{T,\pi}(\hat{z}) dH_{T,\pi}(z)}{\int\int \pi^{\rho} \max\{1,\hat{\pi}/\pi\}^{\beta} d\widehat{M_{\pi}}(\hat{\pi};\pi,\theta) dH_{C,\pi}(z)}.$$

[41] This result is trivially applied given our assumptions used in the main text, where the equation follows directly from $\pi' \propto z'$. However, it is a useful result when we relax functional form assumptions in various extensions, so we highlight it here.

Given β and ρ, the right hand side is continuous in θ by the continuity of $\widehat{M}$ in Assumption 3. The intermediate value theorem then guarantees existence when $\Gamma \in [\Gamma^{min}, \Gamma^{max}]$. Finally, uniqueness follows from the strict monotonicity of the right hand side in θ, which is guaranteed by the assumed first order stochastic dominance in Assumption 3. ■

G.4 Proof of Proposition 4

Proof. Start from the law of motion defined in Assumption 1. In logs, and applying Assumption 2 ($\pi \propto z$) and Assumption 4 ($\hat{z} > z$), this is

$$\log(\pi_i') = \widetilde{c} + \rho \log(\pi_i) + \beta \log\left(\max\left\{1, \frac{\hat{\pi}_i}{\pi_i}\right\}\right) + \varepsilon_i, \qquad \text{(G.5)}$$

where π_i and $\hat{\pi}_i$ are baseline profit for individual i in the treatment group and her match, while $\widetilde{c}$ is a constant equal to the structural parameter c if $\pi = z$. Since matches are observable within the treatment, (G.5) is a simple panel regression with coefficients β and ρ. That $\hat{\beta}^{OLS}$ and $\hat{\rho}^{OLS}$ are equal to their structural counterparts follows directly from the fact that this regression has full rank (Assumption 4assn:dataset:c) and that unobservable shocks ε are orthogonal to π and $\hat{\pi}$ (4 (d)). ■

G.5 Proof of Proposition 8 (from Social Planner's Problem)

Proof. Since these are static decisions, they solve the simplified static problem

$$\begin{aligned}
\max_{c,s,x,n} \quad & \omega \int_0^{\infty} \log(c(z))dM(z) + (1-\omega)\int_{\underline{z}}^{\infty} \log(1-s(z))dM(z) \\
s.t. \quad & \int_{\underline{z}}^{\infty} x(z)^{\alpha} n(z)^{\eta} dM(z) - \left(\frac{1-\eta-\nu(1-\eta-\alpha)}{\alpha}\right) \int_{\underline{z}}^{\infty} exp(-s(z)) z^{\frac{\alpha+\eta-1}{\alpha}} x(z) dM(z) = \int_0^{\infty} c(z \\
& \int_{\underline{z}}^{\infty} n(z)dM(z) = \int_0^{\underline{z}} dM(z) \equiv N_s \\
& M(z) \text{ given}
\end{aligned}$$

Note that for simplicity here, we have already imposed a cut-off value for z, $\underline{z}$. Much like the *laissez faire* equilibrium, it is straightforward to show that the planner also chooses to set occupations this way.

The first piece to note is that, given the separability of utility in c and s, the planner allocates a constant level of consumption $c(z) = c$. Thus, we just need to determine total resources in the economy to determine consumption. Solving the optimal input choices $x(z)$ and $n(z)$ collapses the simplified static planner's problem to

$$\begin{aligned}
\max_{s(\cdot)\geq 0} \quad & \omega \log(c) + (1-\omega)\int_{\underline{z}}^{\infty} \log(1-s(z))dM(z) \\
s.t. \quad & \left(\frac{\alpha^2}{1-\eta-\nu(1-\eta-\alpha)}\right)^{\frac{\alpha}{1-\alpha}}(1-\alpha)N_s^{\frac{\eta}{1-\alpha}}\left(\int_{\underline{z}}^{\infty} z\exp(s(z))^{\frac{\alpha}{1-\alpha-\eta}}dM(z)\right)^{\frac{1-\alpha-\eta}{1-\alpha}} = c \\
& M(z) \text{ given}
\end{aligned}$$

The first order condition for this problem is

$$\frac{(1-\omega)m(z)}{1-s(z)} = \lambda C\left(\int_{\underline{z}}^{\infty} z\exp(s(z))^{\frac{\alpha}{1-\alpha-\eta}}m(z)dz\right)^{\frac{-\eta}{1-\alpha}}\left(\left(\frac{\alpha}{1-\eta-\alpha}\right)z\exp(s(z))^{\frac{\alpha}{1-\alpha-\eta}}m(z)\right)-\lambda_2$$

where λ is the Lagrange multiplier on the resource constraint, λ_2 is the multiplier on the non-negativity constraint $s \geq 0$, and C is the constant in front of the integral of the resource constraint. For any z_1 and z_2 with interior solutions ($\lambda_2 = 0$), we have

$$\frac{1-s(z_2)}{1-s(z_1)} = \left(\frac{z_1}{z_2}\right)\left(\frac{\exp(s(z_1))}{\exp(s(z_2))}\right)^{\frac{\alpha}{1-\alpha-\eta}} \tag{G.6}$$

Define for ease of notation $q(z_2/z_1, s(z_1)) = \left(\frac{z_1}{z_2}\right)\exp(s(z_1))^{\frac{\alpha}{1-\alpha-\eta}}(1-s(z_1))$ and the transformation $-t = \left(\frac{\alpha}{\alpha+\eta-1}\right)s(z_2) - \left(\frac{\alpha}{\alpha+\eta-1}\right)$. After some algebra, we can rewrite (G.6) as

$$\left(\frac{q\alpha}{\eta+\alpha-1}\right)\exp\left(\frac{\alpha}{\eta+\alpha-1}\right) = t\exp(t)$$

The solution to this problem is given by the principal branch of the Lambert W function,

$$t = W_0\left[\left(\frac{\alpha}{\eta+\alpha-1}\right)\exp\left(\frac{\alpha}{\eta+\alpha-1}\right)q\right].$$

Undoing the transformation and setting $z_1 = \underline{z}$, if the economy is at an interior solution to s for all $z \geq \underline{z}$ (which we verify at our estimated parameters), we can write this as

$$s(z_2) = \left(\frac{1-\alpha-\eta}{\alpha}\right)W_0\left[\left(\frac{\alpha}{\eta+\alpha-1}\right)\exp\left(\frac{\alpha}{\eta+\alpha-1}\right)q(z_2/\underline{z}, s(\underline{z}))\right] + 1,$$

Since q is decreasing in z_2 and $\eta+\alpha < 1$, that $s(\cdot)$ is increasing follows from the fact that that W_0 is an increasing function. Concavity similarly follows from properties of W_0. Since W_0 is increasing and $x \exp(x)$ is convex, its inverse W_0 is concave.

■

If there is a corner solution, this analysis remains nearly identical, except one would instead be required to solve for $\hat{z} = argmin_z \; \lambda_2(z) = 0$ instead of $s(\underline{z})$. That is, the z at which supplier search intensity becomes positive. While this is not at issue at our estimated parameters, we of course take this into consideration when counterfactually varying parameters to study how the quantitative implications change.

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