CAUSES AND CONSEQUENCES OF LABOR UTILIZATION: EVIDENCE FROM UGANDAN FIRMS*

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Abstract

Labor underutilization is pervasive in small firms in developing countries, yet its causes and consequences remain poorly understood. Using a novel five-year panel of 2,300 firms in Uganda, we document that firms face substantial and hard-to-predict demand volatility, that capital and labor adjustment costs are large, and that workers spend a significant amount of time idle. We develop and estimate a model of firm input and training choices under demand uncertainty, identifying key parameters using a wage subsidy field experiment. A key mechanism is that training requires upfront fixed investment while workers are paid piece-rates, so higher volatility lowers expected utilization and reduces the returns to training. Counterfactual simulations show that reducing demand volatility raises hiring and training nearly as much as lowering training costs directly, and that the effectiveness of typical development policies to stimulate firm productivity and growth—such as capital grants, management training, and market access interventions—all depend critically on the level of demand uncertainty firms face. Our findings highlight a novel demand-side mechanism limiting human capital accumulation and the effectiveness of policies targeting SMEs in low-income settings.

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1 Introduction

Nothing is more anemic to economic growth than productive resources being left idle. Labor underutilization—the phenomenon of workers being present at the firm but not engaged in productive work—is a pervasive feature of small firms in developing countries. A growing empirical literature documents that utilization rates are strikingly low in Sub-Saharan Africa [Walker *et al.* 2024, Bassi *et al.* 2025]. This stands in sharp contrast to the picture of firms in high-income countries, where capacity utilization fluctuates over the business cycle but remains high on average [Burnside *et al.* 1993; Burnside and Eichenbaum, 1996].

A foundational insight from the macroeconomics literature is that variable utilization is a key margin of adjustment through which firms respond to shocks: firms hoard factors in downturns, keeping workers and machines partially idle rather than incurring adjustment costs, and then respond to positive shocks by intensifying input use [Greenwood *et al.* 1988; Burnside and Eichenbaum, 1996; Basu *et al.* 2006]. In settings where firms face large demand uncertainty and costly input adjustment, input underutilization may arise as a second-best optimum where firms hedge against volatility by keeping idle resources [Cooley *et al.* 1995; Fagnart *et al.* 1999; Boehm and Pandalai-Nayar, 2022].

In this paper, we study the causes and consequences of labor underutilization in small and medium-sized firms in Uganda. We make two main contributions. First, while Walker *et al.* [2024] emphasize input indivisibilities as the source of slack, we document and formalize a distinct and complementary mechanism: demand volatility combined with adjustment costs leads firms to keep resources idle as a buffer against uncertain demand. We provide direct evidence on this mechanism using high-frequency data from a novel five-year panel of firms in Uganda. Second, and most importantly, we go beyond documenting underutilization to trace out its downstream consequences, both for on-the-job training and for the effectiveness of typical development interventions to stimulate firm growth. To do so, we develop a model of firm input and training choice under uncertainty, and we estimate it exploiting for identification a field experiment in which firms were randomly offered wage subsidies to hire and train a new worker. A key mechanism is that training requires upfront fixed investment while workers are paid piece-rates, so higher volatility lowers expected utilization and reduces the returns to training. Our counterfactuals show that reducing demand volatility raises hiring and training by nearly as much as lowering training costs directly, and that capital grants, improved market access, and management training are all substantially less effective when demand uncertainty is high.

Our firm panel is based on a representative sample of 2,300 firms with between 1 and 15 employees (excluding the firm owner) operating in eight small-scale manufacturing and services sectors that are central to employment generation in Uganda: motor-mechanics, electrical wiring, welding, plumbing, construction, hairdressing, tailoring and catering. We conducted a census of such enterprises in 15 urban areas of the country in 2012, and then firms were tracked near

annually over four follow-ups, the last of which took place in 2017.

We collected detailed survey data that allow us to study and link demand uncertainty, adjustment costs, labor utilization, and training. We gathered high-frequency information on both realized sales and firms' perceptions about the distribution of future sales, which we use to construct measures of actual and perceived demand volatility. We also collected detailed rosters of machines and workers, enabling us to examine how quickly both inputs adjust in response to demand shocks. Importantly, for each worker we collected information on a typical product they work on, the time required to complete that product, and the piece-rate payment received for their work on the product. Dividing total monthly earnings by the per-product piece-rate yields an estimate of the number of products completed per month. Multiplying this by the average time spent per product allows us to compute the number of hours effectively worked per month, which forms our key measure of labor utilization. Finally, we collect detailed information on the on-the-job training received by employees.

The firm panel was collected as part of a field experiment where firms were offered different labor market interventions. Some of these treatments involved matching young workers to firms and were analyzed in previous studies [Alfonsi *et al.* 2020; Bandiera *et al.* 2025]. For this paper, we exploit an additional treatment arm included in the original design, where 250 of the firms in our sample were randomly offered a six-month wage subsidy to hire and train a new workers of their choice. As discussed in more detailed below, we use this experimental variation to identify and validate the returns to training in our structural model.

We begin the analysis by establishing novel stylized facts on the demand volatility faced by firms, input adjustment costs, and their implications for labor utilization and training provision.

First, we document that firms face substantial variability in both actual and perceived demand. When asked about their maximum and minimum expected demand over the next six months, the minimum for the average firm is about 30% of the maximum. The same holds true when asking about the expected number of customers. Running fixed effects regressions on realized monthly revenues, we find that the majority of the variability in revenues cannot be explained by firm or sector $\times$ time fixed effects. In short, our evidence points to demand being not only highly variable but also difficult for firms to predict. In contrast, capital and labor inputs display lower and more predictable variability.

Second, we show that adjustment costs in both capital and labor are substantial. Owners report difficulties in accessing the funds needed to purchase additional expensive machines, as well as frictions in finding new workers with the right skills.[1] To validate these self-reports, we exploit our detailed asset and worker rosters to conduct event studies showing that firms adjust their inputs slowly over time following the hiring or firing of a worker, consistent with the presence of adjustment costs. In addition, we show that in response to demand shocks (proxied

[1]Our survey shows that rental markets are not well developed in our sectors of interest, in contrast with the findings of Bassi *et al.* [2022] for the carpentry sector in the same context.

by instrumenting revenues with by the mean revenues of other firms in the same location) firms do not adjust the capital or labor input, and instead adjust labor utilization.

Third, we show that labor underutilization is pervasive. While the average worker spends 269 hours per month at their firm (implying a 60 hour working week), only 84 of these hours are spent engaged in production, implying a utilization rate in production of about 30% for the average firm. Allowing for a utilization rate in non-production tasks of 20% [Bassi *et al.* 2025] brings the estimated overall utilization rate to about 50%, a figure in line with that found by Walker *et al.* [2024] for Kenya.

Fourth, training is an essential way in which firms access skilled workers, and training costs are substantial. Half of the employees in our data have received on the job training at their current employer. Training takes about 9 months and is usually conducted by the firm owner: conditional on having trainees, the average owner spends over 100 hours per month training workers, implying large time costs associated with training provision.

Finally, we bring this analysis together and study the correlation of demand uncertainty with labor utilization and training. We find that firms with more variable (perceived or actual) demand have lower utilization and invest less time in training workers. These results are robust to instrumenting revenue variability with the revenue variability of other firms located nearby. This evidence is consistent with the mechanism we propose: when faced with uncertainty, firms keep resources idle, which lowers the expected returns to paying the fixed costs of hiring and training workers, thereby reducing investment in training.

Building on the stylized facts, we develop a model that links the causes of underutilization—demand uncertainty and input adjustment costs—to its consequences —underinvestment in labor inputs, and in particular training. The model features monopolistically competitive firms making input choices under uncertainty. In the first period, before the realization of an idiosyncratic demand shock, firms set prices and choose capacity by investing in capital, hiring workers, and deciding how much training to provide. In the second period, the demand shock is realized and firms adjust utilization, choosing how intensively to deploy their existing inputs, but cannot adjust capital, employment, or training due to the presence of adjustment costs.

A key feature of the environment is that capital and training investments are fixed and paid upfront, while workers are compensated primarily on a piece-rate basis and are therefore paid only when utilized, as observed in the data. As a result, higher demand volatility reduces expected utilization and lowers the returns to fixed training investments. This creates a novel demand-side channel through which uncertainty discourages firms from investing in workers' skills.

We estimate the model using simulated method of moments. The estimation targets two types of moments. First, we target cross-sectional moments from the baseline and control-group data, exploiting our detailed measures of labor utilization and firm-provided training to identify demand volatility and training costs. Second, we use experimental variation from the wage subsidy intervention to identify the returns to training and workers' labor supply responses, parameters that

would otherwise be subject to endogeneity concerns. The model matches the targeted moments closely.

To further validate the framework, we simulate the wage subsidy intervention in the estimated model and compare the implied treatment effects to those observed in the data. The simulated impacts on employment, training, utilization, and revenues closely track the experimental estimates, providing additional support for the model's ability to capture the key mechanisms linking demand volatility, utilization, and investment in training.

We conduct two sets of counterfactuals. First, we run a horse race between four key frictions that have been proposed as drivers of the low levels of on-the-job training in low-income countries: training costs, high turnover, high demand volatility, and low average levels of demand. To do so, we change the parameters corresponding to these different frictions so as to achieve a 10% increase in sales, and study the corresponding impacts on firm choices of labor input and training. The key result is that reducing demand volatility yields in increase in trained workers that is almost as large as that achieved by reducing training costs or separations— typical channels that the literature has focused on.[2]

Second, and more broadly, we show that demand uncertainty shapes the returns to typical development policies aimed at fostering firm growth. We simulate the effects of capital grants (i.e., reductions in the cost of capital), improved market access (i.e., an increase in the level of demand) or management training (i.e., an increase in firm TFP) across environments with different levels of demand volatility, and show that all these policies yield significantly higher returns for firms when demand volatility is lower, with labor utilization being an important mediating factor. This strong complementarity between demand stability and policy effectiveness suggests that the returns to conventional firm-targeted interventions are substantially mediated by the demand environment in which they are implemented—a dimension that has been largely overlooked in the evaluation literature.

Related Literature and Contribution Our paper contributes to four main strands of the literature. First, we contribute to the literature on underutilization and its macroeconomic implications. Walker et al. [2025] establish that slack is pervasive in low-income economies and has large aggregate consequences for fiscal multipliers and aggregate supply elasticity. We complement their analysis by identifying demand volatility and adjustment costs— distinct from input indivisibilities —as an additional source of underutilization, and by studying its consequences for firm-level investment and human capital accumulation.[3] The macro literature on utilization and

[2]In a similar vein, we show that the effectiveness of wage subsidies to hire and train new workers depend on the level of demand uncertainty. There is a strong complementarity: wage subsidy interventions are more effective when demand is more stable.

[3]Butters [2020] establishes in a developed-country context that demand volatility and adjustment costs generate optimal underutilization and bias standard productivity measures. We extend their analysis to a developing-country setting with very different firm characteristics, study labor rather than capital utilization, and go beyond

shock propagation [Greenwood, *et al.* 1988; Burnside and Eichenbaum, 1996; Basu *et al.* 2006] provides the theoretical foundations for our firm-level framework: the same logic that makes utilization a key margin of aggregate adjustment in rich-country business cycle models operates at the firm level in our setting, but with much larger steady-state slack and qualitatively different consequences.

Second, we contribute to the literature on policies to improve firm performance and stimulate SME growth in low-income countries. A large experimental literature has evaluated capital grants [De Mel *et al.* 2008; Blattman *et al.* 2014; De Mel *et al.* 2019], management training [Bloom *et al.* 2013; Bloom *et al.* 2014; McKenzie and Woodruff 2014, 2017], wage or training subsidies [Alfonsi *et al.* 2020, Hardy and McCasland 2023, De Mel *et al.* 2019, Brown *et al* 2024], and market access interventions [Ali *et al.* 2025], often finding that impacts are positive but modest, and sometimes short-lived. We contribute by documenting a new mechanism that can limit the effectiveness of all these interventions simultaneously: when firms face high demand volatility, they optimally keep resources underutilized, which reduces the returns to any intervention that increases input availability or quality.

Third, we contribute to the literature on the determinants of firm-sponsored training and, more broadly, human capital accumulation in low-income countries [Acemoglu and Pischke, 1998, 1999; Lagakos *et al.*, 2018; Caicedo *et al.*, 2022; Cefala *et al.*, 2025a, 2025b; Ma *et al.* 2024]. This literature has emphasized training costs, worker turnover, and poaching externalities as the primary frictions limiting on-the-job training. We identify a novel demand-side channel: demand volatility reduces expected utilization and therefore lowers the returns to the fixed costs of training, providing a new explanation for why firm-sponsored training is so limited in developing countries and why it responds so little to conventional supply-side interventions.

Finally, we contribute to the literature on misallocation and productivity differences across firms [Hsieh and Klenow, 2009]. That literature focuses on static across-firm misallocation—resources being in the wrong firms—and typically infers distortions from dispersion in marginal revenue products across producers. Recent work has shown that this inference is complicated by endogenous capital utilization: when firms adjust utilization flexibly in response to shocks, dispersion in average revenue products of capital can reflect efficient reallocation of capital services (i.e., utilized labor) rather than misallocation [Kabir *et al.* 2025]. Our paper identifies a further and distinct source of the problem: demand volatility generates within-firm underutilization that not only makes firms appear less productive [Butters, 2020] but actively suppresses the investment in training that would raise long-run productivity. This dynamic channel compounds over time in a way that static misallocation frameworks do not capture.

Structure of the Paper The paper is organized as follows. Section 2 describes our data of firms and the key measurements enabling us to study the causes and consequence of labor under-

measurement implications to examine investment consequences.

utilization. Section 3 presents stylized facts on demand volatility, input adjustment costs, labor underutilization and firm-provided training. In Section 4 we develop a model of firm input choices that reflects the key stylized facts established and uses this to draw implications of this on consequences for firm-sponsored training of workers. Section 5 discusses the estimation and presents results from counterfactuals aimed at assessing the importance of demand volatility for training and the overall effectiveness of firm-targeted interventions in low-income countries. Section 6 concludes.

2 Firm Data

2.1 Sample, Timeline and Attrition

Our data is from a representative sample of firms operating in 15 urban labor markets across Uganda. We drew this sample in 2012, conducting a census of firms and selecting those: (i) operating in one of eight sectors, covering both manufacturing and services: motor-mechanics, electrical wiring, welding, plumbing, construction, hairdressing, tailoring and catering; (ii) having between one and 15 employees (plus an owner). The second restriction excludes micro-entrepreneurs and ensures that we focus on small and medium sized firms that are central to employment generation in Uganda, and that have meaningful choices to make over capital and labor inputs. Our baseline sample, which was part of a two-sided field experiment studying labor markets in Uganda [Alfonsi *et al.* 2020], comprises 2300 firms, that in aggregate employ 6000 workers, with the average firm size being three (plus a firm owner). These firms offer good jobs: earnings are higher in these sectors than many others in Uganda, and they collectively employ about 30% of individuals aged 20-30 working outside of agriculture.

The upper panel of Figure A1 shows the study timeline. The baseline survey of firms took place between December 2012 and June 2013. Firms were then tracked near annually over four follow-ups, the last of which took place between March and July 2017. The lower panel of Figure A1 shows the timing of data collection.

We consider firms to have attrited if they cannot be found by enumerator teams or are known to have shut down. By the fourth follow-up, 32% of firms interviewed at baseline had attrited. Over a four year time frame, this is in line with an annual death rate of 8.2% documented by McKenzie and Paffhausen [2019] for similar SMEs across 12 developing countries. Table A1 shows correlates of attrition at each follow-up: less profitable, smaller and younger firms are all more likely to attrit. Owner characteristics do not predict attrition.

2.2 Data and Experimental Design

Volatility, Utilization, and Training Three features of our data collection allow us to link utilization, demand volatility, adjustment costs, and training. First, we collected data that allows us to recover the number of hours each worker spends in production (more details are provided in Section 3.1). We use this data to construct a measure of labor utilization, which we define as the the number of hours an employee spends on production tasks divided by the number of hours the worker spends at the firm premises. This measure is central to our analysis, allowing us to document the incidence of labor underutilization in our firms and its relationship to demand uncertainty and adjustment costs.

Second, we collected high-frequency data on firm outcomes and inputs. Specifically, we recorded profits and revenues for each of the three months preceding each survey wave. This provides us with 15 data points in total. We use this data, combined with information about the distribution of owners' expectations over profits and revenues, to provide evidence of (perceived) demand volatility *within* the firm and disentangle how much of it is predicted by seasonal effects.

In addition, we collected information to construct monthly rosters of assets and employees. For the asset rosters, we asked owners about the quantity and unit price of each pre-specified, sector-specific assets/machines. We recorded information on all assets firms had access to, regardless of whether they owned, rented, or borrowed the asset. Figure A2 illustrates the asset roster module in four of our study sectors. For the worker rosters, we collected data on each employee's demographics, recruitment process, productivity, hours and earnings. To build a monthly panel of assets and employees of firms, in each follow-up survey, we asked owners whether the firm still employed the assets/employees listed in the previous survey, and recorded information on asset sales/purchases and worker hires/layoffs. This enables us to document input changes over time. In particular, it allows us to examine whether firms adjust their input choices to short-term changes in demand, which we take as evidence of the presence (or absence) of adjustment costs.

Finally, we collect detailed information on training. For each worker, we have data about the type of training received (vocational or on-the-job), the length of the training period at the firm, the monetary cost of training, including the worker's earnings (or the amount of money paid to the owner in the case of workers who pay to receive training) as well as the cost of the materials and tools used during this period. We also record the position of the individual responsible for training (owner or other employees). We use this data to provide evidence that firm-provided training is costly in this setting and to examine how training provision responds to demand volatility.

Wage Subsidy Experiment Our data was collected as part of a two-sided field experiment studying labor markets in Uganda implemented in partnership with the NGO BRAC. Firms in the study were randomly assigned to either (i) be matched with vocationally trained or untrained workers, (ii) be given a wage subsidy to hire and train a new worker, or (iii) be held as a control

group. The vocational training and matching interventions were the focus of two companion papers that focused on the worker side of the experiment [Alfonsi *et al.* 2020, Bandiera *et al.* 2025]. In this paper, we use the wage subsidy intervention and exploit the firm-side data to target key empirical moments and validate the structure of a model of the firm linking demand uncertainty, utilization, and firm-provided training.

As part of this intervention, 256 firms were randomly chosen to be provided with a wage subsidy of UGX 120,000 (approximately $50) per month to hire and train a new worker of their choice. This amount corresponds roughly to the 75th percentile of the distribution of unskilled wages, and owners and workers were left free to negotiate how to split the amount. The subsidy lasted for six months from the time the new employee was hired, conditional on the worker being employed at the firm and present on a regular basis. Figure A5 shows the contract between BRAC and the firm owners who took up the subsidy. While the document specifies that firms were obliged to provide training to workers, it did not specify a curriculum for them to follow. In addition, BRAC implemented monthly spot checks that only monitored attendance. Therefore, firms were effectively free to decide how much training to provide to the new worker.

2.3 Descriptives

Firms Table 1 describes our sample of firms. Panel A focuses on firm and owners characteristics: at baseline, firms are six years old and therefore likely to be in steady state rather than in their start-up phase. Average monthly profits of these firms are $218, enabling them to partially self-finance input purchases. Owners are evenly split by gender, in part because some of the service sectors in our sample are female-dominated.[4]

Panel B describes capital and labor inputs at baseline. The average value of the capital stock accessible to firms is $1256, five times the value of monthly profits. Given firms have three employees on average, this implies a capital stock per worker of over $400. There is very limited sharing of inputs with other firms: only 9% of firms in our study sectors report sharing workers with other firms, and only 12% report sharing machines with other firms.[5]

Panel C describes training within firms: 75% of employees are considered skilled by firm owners, and just over a quarter of these skilled employees were trained by their current firm. At the time of the baseline survey, around one in two firms have an employee undergoing training (suggesting trained workers also exit the firm, potentially being poached by other firms or setting up their

[4]To demonstrate the representative of our sample at baseline, Table A2 compares our sample to those in the 2010 Adult Population Survey conducted by the Global Entrepreneurship Monitor (GEM) for Uganda. The two samples are balanced on most of the comparable characteristics of owners and firms, although our sample is likely to be slightly positively selected given they had to have at least one employee to be eligible for our study. Indeed, firms in our sample place at the 84th percentile of the size distribution of manufacturing and service study sector firms in Uganda.

[5]The lack of asset sharing between firms is in contrast to the evidence in Bassi *et al.* [2022], who document the existence of a large rental market among carpentry firms in Uganda – that is not one of our study sectors.

own firm as the training provided is not entirely firm-specific [Cefala *et al.* 2025a, 2025b]).

Workers Table 2 uses the worker roster data to describe firm employees. We do so for control firms at first follow-up in order to be able to present complete data on training.

Panel A shows that the majority of workers employed by firms in our sample have either received on-the-job training (49.7%) or completed vocational training (26.3%). This is indicative of two things. First, workers require sector-specific skills in order to be productive. This is in line with the high returns to vocational and on-the-job training we document in Alfonsi *et al.* [2020]. Second, due to a limited availability of skilled workers (discussed further in Section 3.3), firms often resort to on-the-job training. However, on-the-job training is far from universal.

Panel B considers compensation schemes. We first note that nearly all employees are full-time. The modal payment mode is piece-rate, with 49% of workers being solely paid according to piece rates and 67% having compensation that includes some fixed payment or payment-in-kind.

Panel C details tenure, hours and earnings. Workers enjoy long tenure within firms – 19 months on average across our study sectors. This highlights that these are long-term and meaningful employment relationships, which further justifies investment in training. Workers spend 11 hours at the firm premises each day, for 25 days a month. This further highlights the fact that workers would have very limited time to work for other businesses. They earn 60$ per month on average – approximately 27% of the owner's profits. However, there is substantial variation across workers, with workers identified as skilled by the firm owner earning 77$ per month on average and 48% of unskilled workers being unpaid.

3 Stylized Facts

We now establish novel stylized facts from our study sectors related to labor underutilization and its potential link to demand volatility faced by firms, input adjustment costs, and training provision. Our objective is to make precise key features of our setting and use these to motivate the modelling framework developed, with the task of understanding the consequences of labor underutilization for firm outcomes and on-the-job training.

3.1 Demand Uncertainty

If firms are unable to easily adjust inputs in response to demand shocks, underutilization may arise as a second best optimum [Cooley *et al.* 1995, Fagnart *et al.* 1999, Boehm and Pandalai-Nayar 2022]. In this subsection we document that firms in our setting face substantial uncertainty over demand, with the bulk of demand volatility being hard to predict. The next subsection provides evidence on input adjustment costs.

To gauge the uncertainty of demand that firms face, we exploit the fact that at first follow-up, we asked owners' their expectations about future revenues and customer numbers. Panel A of Table 3 describes these expectations of revenues for the next six months, and expectations of customer numbers in the next week. We ask: (i) the *minimum* expectation for each outcome; (ii) the *maximum* expectation for each outcome; (iii) the number of months they expect the outcome to be above the midpoint of (i) and (ii). Assuming a triangular distribution of expectations, we then calculate the expected number, standard deviation and coefficient of variation of expectations for each outcome.

Owners face uncertainty along both margins and time horizons. On revenue over the next six months, the lowest expectation is 30% of the highest expectation, with a coefficient of variation of .24. On customer numbers over the next week, the lowest expectation is 33% of the highest expectation. This degree of uncertainty is not specific to our setting: Walker *et al.* [2024] find that among Kenyan micro-enterprises, sales in the worst week were 37% of those in the best week.

While this evidence is consistent with owners facing considerable demand uncertainty, part of the variation could be driven by trends that firms are able to predict, such as seasonality.

To isolate the residual uncertainty, we exploit our panel to regress actual monthly revenues on firm and month by sector fixed effects. Panel B shows the variation in actual monthly revenues. Columns 6 to 8 show that 42% of the variation in actual revenues is explained by time-invariant heterogeneity across firms, and only 3.5% is explained by month by sector fixed effects, capturing sector-specific seasonality. As a consequence, the majority of the variation in actual revenues (55%) remains unexplained, suggesting firms face substantial idiosyncratic demand uncertainty.

In Panel C we present analogous results for realized capital and labor capital inputs. While these fluctuate over time, they do so to a far lesser extent than the variation in actual firm revenues. The coefficient of variation in the value of the capital stock and employee numbers are 50% and 18%, respectively, of the coefficient of variation in revenues. Hence inputs fluctuate substantially less relative to revenues, indicating firms do not fully adjust inputs in response to changes in revenue, but might potentially adjust on the utilization margin. For the value of the capital stock, the vast majority of this variation is explained by time-invariant heterogeneity across firms (98%) and less than 1% remains unexplained. Similarly, variation in employee numbers is largely explained by time-invariant heterogeneity across firms (64%), and only 28% of the variation remains unexplained.

Taken together this evidence reinforces the notion that demand is a key source of uncertainty for firms. It also suggests inputs are more stable and predictable, consistent with the presence of input adjustment costs as we probe further next.

3.2 Adjustment Costs

For demand uncertainty to lead to labor underutilization, it must be costly for firms to adjust inputs. We provide evidence of the nature and existence of adjustment costs, and then develop a measure of relative adjustment costs in labor and capital.

3.2.1 Sources of Adjustment Cost

Capital To begin to understand firm's ability to adjust capital, it is useful to consider the kinds of machine used in our study sectors. Panel A of Figure 2 shows the distribution of machine costs across our firms. To compare across sectors, we normalize machine costs by sectoral averages. The value of most machines lies within a standard deviation of the sectoral average. An asset like lift jacks are a relatively low unit cost machine in the motor mechanics sector; a designing machine is a relatively high unit cost machine in the welding sector.

Panel B details characteristics by quartile of normalized machine costs. We see that: (i) while many firms own assets in the bottom quartile of machine values, fewer than 10% own machines in the top quartile of values; (ii) access to the most expensive machines (through ownership or rental) is more strongly associated with firm profits, perhaps because they allow mechanization and scale-up of activities [Bassi *et al.* 2022]; (iii) over 90% of assets are financed through savings, regardless of the value of the machine.

Panel C shows firm owners' reports at baseline of perceived constraints to expanding capital, the most important being difficulties in finding reliable machines (72%), and high borrowing costs (65%). Both constraints likely bind because of the wide variation in machine values utilized in sectors. The data further reveals time costs are also relevant: searching for the right machine constitutes a substantial time investment for firm owners: (i) 38% of owners searched for machines, spending an average of 23 hours on each search; (ii) 6% of owners search for sources of funding to purchase machines, spending an average of 8 hours on each search.

Labor Panel D repeats the analysis for perceived constraints to expanding the number of workers: finding workers with the right skills (68%), trustworthiness (57%), and being able to assess the quality of applicants (51%) are all key constraints. Fewer owners perceive access to unskilled labor and managerial constraints as key hiring frictions (29% and 21% respectively). Overall, high search and screening costs constrain firms adjusting labor in response to demand shocks [Cooper, Haltiwanger and Willis 2006] – they then face the alternative of training workers in-house in response to such shocks.

3.2.2 Existence of Adjustment Costs

Moving beyond the stated perceptions of owners, we use two strategies to dig deeper on the existence of substantial adjustment costs based on actual input choices.

Our first approach considers how firms' capital, labor, and labor utilization respond to exogenous changes in demand measured through firm revenues. We do so using a Hausman-style instrument, so instrumenting for firm revenues with the average revenues of firm's in the same sector-location-month, excluding the firm's own revenues [Hausman *et al.* 1994, Hausman 1996]. Using our firm panel, we regress inputs on instrumented firm revenue, conditional on firm fixed effects – so removing the time-invariant heterogeneity that explains much of the variation in revenues across firms, and only focusing on the within-firm variation in labor utilization across workers.

These IV results are in Table 4. In line with the presence of adjustment costs, we find the elasticity of labor and capital to demand shocks to be very low – at .004 (Column 1) and −.003 (Column 2) respectively, and neither being statistically different from zero.

To segway towards understanding whether demand shocks translate into changes in labor utilization. Columns 3 first confirm the earlier results on employees hold when we restrict the sample of firms for which labor utilization rates can be constructed. Column 4 however suggests that these firms may face lower capital adjustment costs, as their assets positively respond to demand shocks, with an elasticity of .14. Finally, in Column 5 we examine whether the average labor utilization across workers in the firm responds to exogenous shifts in demand (where we use the average utilization within firms because Table A3 already showed that utilization rates do not vary across workers in the same firm). In sharp contrast to assets or employee numbers, we find that firms significantly increase labor utilization rates in response to positive demand shocks, with an estimated elasticity of .830. In short, firms respond to demand shocks not by changing input levels, but by changing labor utilization.[6]

Our second approach uses an event study design to show how capital, labor, and the value of capital per worker adjust in response to: (i) the hiring/separation of a worker; (ii) the purchase/sale of a machine. To construct these event studies, we use the monthly panel data on the number of workers and the value of assets utilized by firms i in month t and survey wave s to estimate the following specification:

$$y_{it} = \alpha_i + \gamma_t + \sum_{m=-10, m\neq 0}^{10} \beta_m z_{i,t+m} + \varepsilon_{it}. \tag{1}$$

For each survey wave we identify the event as the hiring/separation of a worker, or the purchase/sale of a machine. z_{it} is an indicator equal to one for firms that change inputs in periods after the first input change. α_i and γ_t are firm and month fixed effects respectively.

Figure 3 shows the event studies related to changes in labor. Panel A shows how inputs change around the event of a worker separation: (i) firms do not hire other workers to quickly replace

[6]We can also construct average labor utilization rates separately for skilled and unskilled workers. Doing so we find that positive demand shocks only translate into increased labor utilization of skilled workers: the estimated elasticity from the IV specification is 1.01 for skilled workers ($p = .016$) and −.314 for unskilled workers ($p = .699$). However, we need to caveat this by restating that there are few unskilled workers for whom labor utilization rates can be constructed because most workers are skilled, and unskilled workers are more likely to be unpaid or be paid a fixed wage rather than a piece-rate.

separating workers; (ii) the value of the firm's capital stock changes smoothly around the event – suggesting the separation is unrelated to market conditions limiting firm's capital accumulation; (iii) as a result of both trends, the value of capital per worker ratio jumps upwards around the event. Panel B in Figure 3 shows very symmetric impacts of a new worker hire: capital adjusts slowly and the value of capital per worker never recovers to its pre-hire level.[7]

Figure 4 shows event studies related to changes in capital. Panel A shows the event of a sale of a machine. Such events lead only to a small fall in the value of the capital stock, suggesting most firms only sell small-valued machinery – that they are more likely to own and that is easier to replace. Panel B repeats the analysis for the purchase of a machine. For this event we see a gradual increase in labor around the event but again because the value of these purchases is small, the value of machines per worker falls and does not recover back to its pre-event level.[8]

The key takeaway from these event studies is that it takes considerable time for firms to adjust a given input around the event of a sudden change in the level of the other input, even when that change can be anticipated. In Appendix A3 we construct a proxy for adjustment costs and show that firms facing higher capital or labor adjustment costs are indeed less likely to adjust those inputs in response to a demand shock. Overall, our evidence is all indicative of the existence of substantial input adjustment costs in this setting.

3.3 Labor Utilization

We now document the extent of labor utilization across firms. We exploit our worker rosters to define the labor utilization of worker i employed at firm j in the last month as:

$$\text{Labor utilization}_{ij} = \frac{\text{number of hours spent by } i \text{ engaged in production tasks at firm } j}{\text{number of hours spent by } i \text{ at firm } j \text{ premises}}. \quad (2)$$

The numerator is constructed using information on: (i) the piece-rate the worker received to complete a pre-identified sector-specific product/service; (ii) the time it typically takes them to complete that sector-specific product/service; (iii) the workers' total monthly earnings in the month prior to the survey. We calculate the number of products/services the worker completed in the previous month by dividing total earnings by the piece-rate. We then derive the number of monthly hours spent in production as the number of products/services the worker produced times the typical product/service-specific time taken by them to complete the task. We are thus

[7]These findings do not vary with the reason for separation. Figure A4 shows similar results from event studies where the worker left voluntarily or was fired. The slight difference is that in the latter case we see more evidence of firms replacing the worker around seven months after their departure. This might be because firms start searching for a new employee before firing an old one, in anticipation of the time required to find a replacement.

[8]Outside of these events related to labor and capital inputs, we can also document the share of firms that adjust labor and capital inputs from one survey wave to the next (exploiting the worker and asset rosters). This is shown in Table A5 where we see that: (i) adjustments in the number of workers are more frequent that in machines; (ii) for both inputs, positive and negative adjustments occur with similar frequency across all survey waves.

able to measure labor utilization for workers that: (i) are paid a piece rate, and, (ii) engage in the pre-identified sector-specific product/service. This information is consistently available from the second follow-up onwards.[9]

For transparency, Table A3 details the sample of firms and workers that our measure of labor utilization can be constructed for. Column 1 considers characteristics of firms in which the labor utilization measure can be constructed for at least one worker, conditional on sector. We can construct our labor utilization measure for 60% of firm-survey observations. As expected, firms with more unskilled workers are less likely to be used to construct this outcome, because unskilled workers are less likely to be paid piece rates. The next two Columns repeat the analysis based on worker characteristics. Column 2 shows that we are able to construct labor utilization measure for 48% of workers: and we are more likely to do so for skilled or higher productivity workers. Column 3 shows this conclusion is unchanged conditional on firm fixed effects.

Panel A of Figure 1 plots the distributions of the number of hours that workers spend engaged in production tasks in the month prior to baseline (light blue), and the hours spent at the firm premises over the same month (dark blue). Panel B then shows the distribution of the labor utilization rate. The *underutilization* of labor is pervasive: while the average worker spends 269 hours per month at their firm (implying a 60 hour working week), only 84 of these hours are spent in them engaging in production tasks: implying a labor utilization rate of 31%. The distribution is right skewed: at the extremes, only 1% of workers have a utilization rate above .9, and 22% have utilization rates below .1. Figure A3 plots labor utilization rates for workers in each sector, demonstrating the phenomena is not driven by a subset of sectors: labor utilization rates vary from .16 in plumbing to .57 in catering. It also shows that there is substantial variation in utilization rates across workers in the same sector, who conduct similar tasks.

Interpretation and Validation Three points are of note. First, a caveat to our measure of underutilization is that it does not include the time workers spend on non-production tasks, such as procuring inputs, interacting with customers, or cleaning the firm premises. Using data from the same setting and similar sectors, Bassi *et al.* [2025] document that employees spend 20% of their time on such non-production tasks. Assuming such tasks are conducted to the same extent in on our study sectors, the average labor utilization rate in our setting would rise to 51%.

[9]For each worker paid by piece-rates (67% of workers), we ask them to identify the sector-specific product or service the worker performs most often. We then asked the following questions regarding the product or service identified by the worker: (i) *How much time (in minutes) would <name> normally take right now to complete his/her work on this product/service alone to a standard of quality considered satisfactory by the average customer of this business?*; (ii) *How much of the price charged to customers for this product/service does <name> normally receive?* The implicit assumption behind the construction of our labor utilization measure is that the piece-rate on other tasks is proportional to the amount of time the worker spends on those other tasks. We can also construct the labor utilization measure at first follow-up but with slightly more imprecision. Specifically, at first follow-up, we pre-specified a task when we asked firms about the time it would take a worker to complete it, but not when asking about the piece-rate paid to workers for the task. This implies that the tasks to which these two questions refer might be different. Starting from the second follow-up, we asked both questions about the same task.

This figure is in line with the level of underutilization documented by other studies in the same context. First, it is consistent with a recent study conducted by the Uganda Manufacturing Association and the Uganda Small Scale Industry Association [UMA 2023], which finds an average utilization rate of 54.4% among a random sample of 205 manufacturing firms that are members of the two organizations. Second, the figure is only slightly lower than the 60% utilization rate documented by Walker *et al.* [2024] in micro-enterprises in Kenya. However, our measure of the time workers spend on production tasks is substantially lower than the 60% reported by Bassi *et al.* [2025] for the carpentry sector. Two things are worth noting regarding this comparison. Our sample includes firms across eight sectors spanning both manufacturing and service activities. On average, our data shows that utilization rates are almost 8 percentage points higher in manufacturing relative to service sectors. In addition, UMA [2023] shows that furniture, which is the focus of Bassi *et al.* [2025] and is not part of our study, is the manufacturing sector with the highest utilization rate (89%) among the 19 sectors from which they collect data.

Second, we find limited evidence that when not utilized, workers spend time at other firms. As mentioned earlier, only 9% of firms report sharing workers with other firms, and 94% of workers are employed full-time. The fact that workers remain idle rather than being re-employed in other firms is natural given the sporadic flow of customer arrivals, implying that workers could be called upon at unpredictable times. We expand on this below, as we probe the role of demand uncertainty as a potential cause of labor underutilization.

Finally, in Table A4 we explore whether owners also have idle time using data on owners' time use. We note that: (i) 85% of owners report being at the premises every day; (ii) they then spend just under 11 hours working on site in a typical day; (iii) owners thus report little idle time at work, where they report allocating time to training, assisting or searching for workers, or searching for machines and loans.

Labor Utilization of Workers Within Firms Given our measure of labor utilization is constructed at the worker level, we can examine how individual characteristics correlate to utilization rates. These results are in Columns 4 and 5 of Table A3. In Column 4 we control for worker characteristics, and fixed effects for survey waves, location and sector. Worker characteristics are not predictive of utilization rates – the only statistically significant predictor is tenure within the firm, but the magnitude of the partial correlation is very small. In Column 2 we control for survey wave and firm fixed effects to narrow in on within-firm variation in labor utilization: we see a very similar pattern of results. Specifically we do not see that skilled, more educated or longer tenure workers have higher labor utilization rates. Nor do we find evidence of family members employed by firm owners being utilized less. This suggests the underutilization of labor in our study sectors is not reflecting using the offer of work as a form of redistribution whereby family members are employed but left unused [Macchi and Stalder 2024, Swanson 2025].

3.4 Training costs

In the previous sections, we documented that on-the-job training is common in our sample: roughly half of workers have received training within the firm (Table 2, Panel A). Most of this training takes place at the beginning of the employment relationship and lasts several months, suggesting it constitutes a large fixed investment by the firm. In what follows, we document that providing this training entails substantial costs for firms.

We use detailed survey data to provide evidence on the type of costs firms incur to provide the relevant skills to thier workers. In particular, Table 5 reports training costs split into three categories: (i) labor costs, namely the wages paid to trainees; (ii) time costs, namely the time that the firm owner and other employees invest in training each worker; and (iii) the cost of the tools and materials required for training.

Turning first to labor costs, we observe a variety of arrangements: the majority of trainees are unpaid, 29% of trainees pay owners for their training, and 20% of trainees are paid during their training. This suggests that monetary transfers between owners and trainees are not the primary cost of training.

Instead, the time costs of training are substantial and fall predominantly on firm owners. On average, training a worker takes 9 months. Firm owners are involved in over 90% of trainings, with the remaining cases being where training is conducted only by co-workers of the trainee. Conditional on having trainees, owners spend more than 110 hours per month training workers. This represents almost 40% of the time that the owner spends on the firm premises, in line with the primary cost of training being the opportunity cost of time – particularly the time of the firm owner.[10]

Finally, there are important training costs related to the purchase of tools or materials for trainees in our study sectors: these are relevant in over 80% of trainings, and paid for by owners 56% of the time.

3.5 Labor Utilization, Demand Uncertainty and Training

We now bring all the analysis together to examine how demand uncertainty correlates with labor utilization and training. Table 6 shows the relevant partial correlations. In Column 1 we regress labor utilization on our measure of demand uncertainty: the coefficient of variation of firms' *expected* monthly sales as measured at first follow-up, controlling for sector and location fixed effects. We find a precisely estimated negative partial correlation between demand uncertainty and labor utilization.

We next exploit the panel data to regress labor utilization on the coefficient of variation of

[10]The number of monthly hours owners spend training their workers is 50, corresponding to 17% of the time they spend at the firm. This figure is very close to the 15% reported by Bassi *et al.* (2024) for similar firms in the carpentry and welding sectors in Uganda.

firms' *current* monthly revenues, controlling for firm fixed effects. This OLS specification shows a negative, but not statistically significant, relationship between demand volatility and labor utilization. To establish a causal relationship,we instrument the coefficient of variation of firms' current monthly revenues with the average coefficient of variation of monthly revenues among firms in the same sector, location and survey wave, excluding the firm itself. The IV result in Column 3 shows a negative partial correlation between demand volatility and labor utilization. The magnitude of the coefficient implies that a one standard deviation increase in the coefficient of variation of monthly revenues is associated with a 0.05, or an 18% decrease in labor utilization.

In short, the negative relationship between demand volatility and labor utilization holds both across (Column 1) and within firms (Columns 2 and 3). Table A6 breaks down labor utilization by the number of hours spent in production (Columns 1 to 3) and the number of hours spent at the firm premises (Columns 4 to 7). It shows that the effects on utilization are driven by changes in the hours workers spend on production tasks rather than by adjustments in hours spent at the premises. Overall, the results are consistent with firms facing higher demand uncertainty maintaining idle resources to be able to quickly scale up and absorb positive demand shocks [Cooley *et al.* 1995, Fagnart *et al.* 1999, Butters 2020]. In contrast, firms facing more stable demand are better able to predict their input needs and have a lower option value of keeping inputs underutilized.

Columns 6 to 8 show results from the same regression specifications, but using the number of hours the owner spent training workers in the month prior to the survey as the outcome. Column 6 shows that, at baseline, firm owners facing higher uncertainty about future revenues spend significantly fewer hours training workers. Column 8 focuses on within-firm variation, using the same IV for revenue volatility described above. It shows that, when faced with an exogenous increase in uncertainty, owners decrease the amount of time they dedicate to training workers. The magnitude of the coefficient implies that a one standard deviation increase in the coefficient of variation of monthly revenues is correlated with a 6 hours, or a 12% decrease in the number of hours the owner spent training in the last month.

Both these results are consistent with the returns to training being lower when firms face greater demand uncertainty. This is because firms pay a fixed cost to train employees – a cost that is independent of subsequent utilization. However, as shows in Columns 1 to 3, workers are utilized less intensively when uncertainty rises, which reduces the returns from training. Two points are worth noting. First, Columns 8 to 10 in Table A6 show that this result is not driven by changes in the time owners spend at the premises. Second, if demand uncertainty also led to an increase in the owner's idle time, we might expect a positive within-firm relationship between volatility and training, as owners would have more time available to train workers. Although we do not rule out that this mechanism may operate, the results suggest that it is more than offset by the reduced incentives to train workers who are expected to be underutilized.

4 Model

We now build a model that incorporates the key stylized facts established in the previous section: that fundamental frictions related to demand uncertainty and adjustment costs can impact utilization rates and firms' input choices. We focus in particular on the consequences these features have for firms' investment in training. To do so, we build a model that incorporates standard mechanisms the literature has explored as limiting on-the-job training – high training costs and the possibility of workers leaving the firm after being trained – along with the novel utilization channel. We then estimate the model using our rich data and exogenous variation from the wage subsidy experiment. We run counterfactuals with two objectives in mind: (i) benchmarking standard explanations for firms' low investment in training against a new potential channel – demand volatility and the resulting input underutilization; (ii) assessing how the effectiveness of different types of firm-targeted policies is affected by uncertainty about future demand.

4.1 Set-up

The economy features monopolistically competitive sector, with a continuum of homogeneous firms $j \in J$ producing differentiated varieties, and homogeneous risk-neutral workers $i \in I$. The model has two periods.

1. Period 1: Both firms and workers face uncertainty about demand. Firms choose capital k_j, the number of workers b_j, training τ_j, and price p_j. Workers choose the amount of time to spend on the premises h_j.

2. Period 2: The idiosyncratic demand shock v_j realizes. k_j, b_j, τ_j, h_j are fixed, but firms can adjust utilization by choosing the share of workers' time allocated to production l_j.

The two-period setup provides a simple way to embed the type of adjustment costs observed in the data, which show that it takes time for firms to find and train new workers and to purchase new capital assets.

Demand The model is in partial equilibrium, so we do not explicitly model final consumption. Instead, we assume that each firm j faces an (exogenous) demand function:

$$y_j(p_j, v_j) = \begin{cases} p_j^{-\theta} v_j & \text{if } v_j \leq \tilde{v}_j \\ q_j & \text{otherwise} \end{cases} \tag{3}$$

where v_j is an idiosyncratic demand shock drawn from $F(v)$ with support $v \in [\underline{v}, \bar{v}]$ and $0 < \underline{v} < 1 < \bar{v}$. Let μ_v and σ_v denote the mean and standard deviation of v_j, respectively. Firms cannot produce beyond their capacity q_j. The cutoff shock $\tilde{v}_j = q_j p_j^{\theta}$ is the realization of the demand shock at which unconstrained demand equals capacity.

Production Function In period 1, firms invest in capacity by choosing capital, number of workers, and training, and set prices. Inputs become productive only at the beginning of period 2 (e.g., due to capital installation and worker training time). The firm's productive capacity is given by a constant-returns-to-scale Cobb-Douglas technology:

$$q_j = A_j k_j^{\alpha} (h_j b_j \phi(\tau_j))^{1-\alpha} \tag{4}$$

where $\phi(\tau)$ is the training-augmentation factor, which is assumed to be increasing and concave ($\phi' > 0$, $\phi'' < 0$), and h_j is the share of time firm j's workers spend on the premises.

In period 2, the idiosyncratic demand shock v_j is realized. Inputs are fixed, but the firm can adjust utilization by choosing utilized labor $l_j \in [0, b_j]$. Interpret $\frac{l_j}{b_j}$ as the share of scheduled time a worker actually spends in production, namely the *utilization rate*. Following Fagnart *et al.* [1999], we assume that output with utilization l_j is proportional to the utilization rate, namely:

$$y_j \;=\; q_j \frac{l_j}{b_j} \;=\; A_j \, k_j^{\alpha} \, (h_j \phi(\tau_j))^{1-\alpha} \, b_j^{-\alpha} \, l_j \tag{5}$$

Three observations follow. First, this functional form implies that all inputs are idled in the same proportion, or, in other words, that there is no separate choice of capital and labor utilization. Second, the marginal product of utilized labor, $\partial y_j / \partial l_j = q_j / b_j$, is increasing in capital (k_j) and training (τ_j), reflecting complementarity in the technology, as well as in workers' time on the premises (h_j). Third, $\partial y_j / \partial l_j$ decreases in b_j, which implies that adding workers raises capacity but dilutes the payoff from additional utilization. This could reflect coordination costs that increase with team size, whereby larger teams require greater communication and agreement across workers [Becker and Murphy 1992, Bassi *et al.* 2024]. These costs are likely to be larger in slack states, when workers must decide not only how to allocate tasks but also who works and who does not, particularly in an environment where workers are paid only when performing tasks.

4.2 Firm input and price choices

We solve the model by backward induction.

Labor utilization Given a realization of the demand shock v_j in period 2, the firm's optimal production choice is to adjust labor utilization to meet its production needs. This is because, as shown below, optimal prices exceed marginal cost, so it is optimal to produce as much as possible subject to demand and capacity. The optimal utilized labor is therefore:

$$l_j \;=\; \frac{y_j}{A_j k_j^{\alpha} (h_j \phi(\tau_j))^{1-\alpha} b_j^{-\alpha}}, \qquad 0 \le l_j \le b_j \tag{6}$$

Price Prices are chosen before observing v_j. Let $\text{MC}_j \equiv \frac{wh_j}{A_j k_j^\alpha (h_j \phi(\tau_j))^{1-\alpha} b_j^{-\alpha}}$ denote marginal cost. Expected profit is:

$$\max_{p_j} \; E_v\big[\big(p_j - \text{MC}_j\big)\, y_j(p_j, v)\big] \tag{7}$$

Using $E_v[y_j(p_j, v)] = p_j^{-\theta} \int_{\underline{v}}^{\tilde{v}_j} v dF(v) + q_j(1 - F(\bar{v}))$, the first-order condition yields:

$$p_j \;=\; \underbrace{\left(1 - \frac{E_v[y_j(p_j, v)]}{\theta\, p_j^{-\theta} \int_{\underline{v}}^{\tilde{v}_j} v\, dF(v)}\right)^{-1}}_{\text{markup } \mu(\tilde{v}_j)} \frac{w}{A_j k_j^\alpha \phi(\tau_j)^{1-\alpha} (h_j b_j)^{-\alpha}} \tag{8}$$

The optimal price is a markup over marginal cost, with the markup $\mu(\tilde{v}_j)$ decreasing in the probability of spare capacity. Intuitively, when a low demand state (relative to capacity) is likely to occur, cutting price expands expected sales in the unconstrained region, so optimal markups are smaller. Conversely, when the firm is often capacity constrained, the firm can sell what it can produce at a higher price, so optimal markups are higher.

Capital, blueprint labor, training In period 1, before observing v_j, firms choose capital k_j, blueprint labor b_j, and training τ_j to maximize:

$$\max_{k_j, b_j, \tau_j} E_v[\pi_j] = E_v[p_j y_j - w h_j l_j - \chi_j(\tau_j) b_j - r k_j] \tag{9}$$

$\chi_j(\cdot)$ is the per-worker training cost, assumed increasing and convex ($\chi_j' > 0$, $\chi_j'' > 0$) and heterogeneous across firms. Using equation (6) and the expression for expected output $E_v[y_j]$, we can rewrite the previous expression as follows:

$$\begin{aligned}\max_{k_j, b_j, \tau_j} \left(p_j - \frac{w}{A_j k_j^\alpha\, \phi(\tau_j)^{1-\alpha}\, (h_j b_j)^{-\alpha}}\right) \left[p_j^{-\theta} \int_{\underline{v}}^{\tilde{v}_j} v\, dF(v) + A_j k_j^\alpha \left(\phi(\tau_j)\, h_j b_j\right)^{1-\alpha} \big(1 - F(\tilde{v}_j)\big)\right] \\ - \chi_j(\tau_j)\, b_j \;-\; r\, k_j\end{aligned} \tag{10}$$

The first order condition with respect to blueprint labor b is:

$$(\mu(\tilde{v}_j) - 1) \frac{w}{A_j k_j^\alpha\, \phi(\tau_j)^{1-\alpha}\, (h_j b_j)^{-\alpha}} \frac{q_j}{b_j} \left[\frac{\alpha(1-\theta)}{\tilde{v}_j} \int_{\underline{v}}^{\tilde{v}_j} v\, dF(v) + \big(1 - F(\tilde{v}_j)\big)\right] = \chi_j(\tau_j) \tag{11}$$

This expression highlights the trade-offs from hiring an additional worker. The first term in brackets (negative for $\theta > 1$) captures the reduction in the marginal productivity of utilized labor due to a larger workforce. The second term captures the increase in capacity from a higher b. The right-hand side is the per-worker training cost.

The first order condition with respect to training τ is:

$$(\mu(\tilde{v}_j) - 1) \frac{w}{A_j k_j^{\alpha} \phi(\tau_j)^{1-\alpha} (h_j b_j)^{-\alpha}} \frac{q_j \phi'(\tau_j) (1-\alpha) (\theta - 1)}{\phi(\tau_j) \tilde{v}_j} \int_{\underline{v}}^{\tilde{v}_j} v \, dF(v) = \chi_j'(\tau_j) b_j \tag{12}$$

The left-hand side captures the marginal benefit of training: a higher $\phi(\tau_j)$ raises the marginal productivity of utilized labor. Training also expands capacity by reducing the amount of labor required to produce a given output. However, this effect is offset by a reduction in optimal prices induced by the lower marginal cost. The right-hand side is the marginal cost of training, which is the equal to the marginal cost per worker times the number of workers employed by the firm.

Finally, the first order condition with respect to capital is:

$$(\mu(\tilde{v}_j) - 1) \frac{w}{A_j k_j^{\alpha} \phi(\tau_j)^{1-\alpha} (h_j b_j)^{-\alpha}} \frac{q_j \alpha (\theta - 1)}{k_j \tilde{v}_j} \int_{\underline{v}}^{\tilde{v}_j} v \, dF(v) = r \tag{13}$$

As for labor, the left-hand side is the marginal benefit from an extra unit of capital, which increasees the marginal product of utilized labor; the marginal cost is the rental *rate* of capital.

4.3 Worker labor supply choice

Workers choose the amount of time to spend at the firm h_j to maximize expected earnings net of the disutility from time at the firm. This disutility captures the value of leisure or the worker's outside options (e.g., leaving to work for other firms or for own customers). For each unit of time spent at the firm, workers only get paid for the fraction of time they are utilized, which we assume is constant across workers and equal to the firm's utilization rate.[11]

Workers choose h_j before observing the realized demand shock v_j and solve:

$$\max_{h_j} E_v \left[w h_j \frac{l_j}{b_j} - \gamma_1 h_j^{\gamma_2} \right] \tag{14}$$

where $\gamma_1 > 0$ and $\gamma_2 > 1$ capture the disutility from time spent at the firm. The first-order condition with respect to h is:

$$h_j = \Big[\frac{w}{\gamma_1 \gamma_2} \Big(\frac{1}{\tilde{v}_j} \int_{\underline{v}}^{\tilde{v}} v dF(v) + 1 - F(\tilde{v}_j) \Big) \Big]^{\frac{1}{\gamma_2 - 1}} \tag{15}$$

At the optimum, h increases with the wage w and decreases with the marginal disutility of time spent at the firm γ. Expected utilization also increases h, as it raises the marginal value of time spent at the firm relative to the outside option.

[11] This is consistent with the data showing that workers are primarily paid piece-rate, as well as with the evidence that there is not much variation in the utilization rate of different workers within the same firm (Table A3).

4.4 Comparative Statics with respect to Demand Volatility σ_v

In this section, we present comparative statics of (i) expected utilization, and (ii) inputs choices (k, b, τ, and h) with respect to demand volatility (σ_v). For expositional purposes, we suppress the firm index j. We also assume that $v \sim \text{Lognormal}(\mu_v, \sigma_v^2)$. We denote by $M_1(\tilde{v}) = \int_{\underline{v}}^{\tilde{v}} v dF(v)$ the conditional expectation of v below the capacity cutoff $\tilde{v}$, and by $\bar{F}(\tilde{v}) = 1 - F(\tilde{v})$ the tail probability above the cutoff.

Let $u = \frac{l}{b}$ denote utilization. Expected utilization can be written as: $E[u] = \frac{M_1(\tilde{v})}{\tilde{v}} + \bar{F}(\tilde{v})$.

Proposition 1 (Utilization vs. volatility, inputs fixed). Hold (k, b, τ, h) fixed and let the firm set price optimally. If (i) the cutoff $\tilde{v}$ is not too far above the mean, $E[v] \leq \tilde{v} \leq E[v]e^{\sigma_v^2/2}$, and (ii) markups are weakly increasing in volatility, $\varepsilon_\mu \equiv \frac{d}{d\sigma_v} \ln \mu(\tilde{v}) \geq 0$. Then

$$\frac{d}{d\sigma_v} E[u] \; < \; 0.$$

The proof is in Appendix 2.1. The intuition, illustrated in Figure A6, is the following: as volatility σ_v rises (holding the mean fixed), the two components of expected utilization respond differently. The slack-state term $\frac{M_1(\tilde{v})}{\tilde{v}}$ decreases whenever $\tilde{v} \geq E[v]$, because higher volatility thickens the left tail of the distribution and lowers the conditional mean of v in states where demand is below capacity. The capacity-state term $\bar{F}(\tilde{v})$ may rise or fall with σ_v: for lognormal demand it increases only if $\tilde{v}$ is extremely large ($\tilde{v} > E[v]e^{\sigma_v^2/2}$), and otherwise decreases. If $\tilde{v}$ is moderate (below the threshold), then both terms move downward with volatility, so expected utilization falls unambiguously. If instead $\tilde{v}$ is very large, volatility fattens the right tail enough that capacity constraints bind more often, and the rise in $\bar{F}(\tilde{v})$ can outweigh the decline in $\frac{M_1(\tilde{v})}{\tilde{v}}$, leading expected utilization to increase.

Proposition 2 (Firm inputs vs. volatility). Let the firm re-optimize (k, b, τ, p) when σ_v changes, holding h constant. Assume (i) $\tilde{v} \geq E[v]$ (so $\partial \ln M_1 / \partial \sigma_v < 0$ at fixed $\tilde{v}$), and (ii) the distributional factor falls with volatility,

$$\frac{d}{d\sigma_v} \ln \Xi(\sigma_v) \; < \; 0, \qquad \Xi(\sigma_v) \equiv (\mu(\tilde{v}) - 1) \frac{M_1(\tilde{v})}{\tilde{v}}.$$

Then training strictly decreases with a mean-preserving change in demand volatility, $\frac{d\tau}{d\sigma_v} < 0$. Capital decreases provided blueprint labor does not rise "too fast":

$$\frac{dk}{d\sigma_v} < 0 \quad \text{whenever} \quad \frac{d}{d\sigma_v} \ln b \; < \; -\frac{d}{d\sigma_v} \ln \Xi(\sigma_v) \; (> 0).$$

The comparative static for b is generally ambiguous.

The proof is in Appendix 2.2. The intuition is as follows. Capital and training only pay in the region where firms are not capacity constrained, as they increase the productivity of utilized labor. However, as the conditional mean of v in that region decreases with σ_v (due to $\frac{\partial M_1(\tilde{v})}{\partial \sigma_v} < 0$), their marginal value falls. Since capital rental and training costs are fixed, namely they are independent of utilization, firms decrease their optimal investment in k and τ when demand volatility increases.

An in increase in blueprint labor b has two effects: it expands capacity q, but it also raises marginal costs and therefore prices. The effect of volatility on optimal b is ambiguous because these two channels work in opposite directions. In the *capacity region* ($v > \tilde{v}$), additional blueprint labor raises capacity q, which is strictly valuable when large demand shocks occur. In this region, the firm already sells up to capacity, so a higher price does not reduce quantity; hence the benefit of extra capacity is not offset by the induced price increase and firms are incentivized to increase b. In the *slack region* ($v < \tilde{v}$), output is demand-determined ($y(v) = p^{-\theta}v$). Here, more blueprint labor raises the marginal cost and therefore the optimal price due to coordination costs, leading to lower demand and sales. Thus, in slack states, increasing b lowers profits. A rise in volatility increases the probability of both very low and very high demand shocks, amplifying both effects. Since the capacity channel pushes b up while the slack-state channel pushes b down, the net effect of volatility on b is *ambiguous*.

Proposition 3 (Workers' time vs. volatility). Suppose (i) $E[v] \leq \tilde{v} \leq E[v]e^{\sigma_v^2/2}$, and (ii) $\varepsilon_\mu \equiv \frac{d}{d\sigma_v} \ln \mu(\tilde{v}) \geq 0$. Then

$$\frac{d}{d\sigma_v} h \; < \; 0.$$

Equation (15) shows that the time workers spend at the premises h is increasing in utilization. As stated in Proposition 1, expected utilization decreases with demand volatility when conditions (i) and (ii) hold. Hence, h decreases with demand volatility under the same conditions.

5 Estimation and Counterfactuals

5.1 Model Estimation

We jointly estimate the model parameters using simulated method of moments and indirect inference.[12] Specifically, we estimate the following nine parameters, $\{\alpha, \theta, \chi, \phi, \sigma_v, \gamma_1, \gamma_2, A, w\}$, by matching the nine data moments listed in Table 7.

Cross-section Moments While there is no one-to-one mapping between an individual moment and a specific parameter, Table 7 indicates which moments are more closely related to the identi-

[12]The returns and the cost of training are parameterized as $\phi \log(1+\tau)$ and $\chi\tau^2$, respectively. We assume the demand shock follows a log-normal distribution with μ_v normalized to 0.

fication of each parameter targeted in the estimation. We highlight a few of these moments, for which some of the unique features of our data collection are essential.

The first one is the average labor utilization rate. The moment we target is the observed share of time workers spend in production in our data, combined with the share of time they spend in non-production tasks in the data from Bassi *et al.* [2025]. This moment allows us to identify demand volatility. The second is the share of workers who receive on-the-job training, which we use to identify average training costs. The rental rate of capital is calibrated externally from Bassi *et al.* [2022], while wages and the return to labor in the production function (α) are estimated by targeting the number of workers and the labor share of firms' costs. While wages may seem high relative to the rental rate, it is important to note that these wages are only paid per unit of time the worker is actually utilized, and would therefore be much lower if they were spread across the number of hours workers spend at the firm. The number of machines employed by the firm allows us to pin down TFP through the effect of productivity on firm scale. Finally, we calculate markups as the ratio of firm monthly profits to total costs (calculated as revenues minus profits).

Experimental Moments We use the experiment to target two additional parameters. The first (ϕ) captures the returns to training. Since understanding the consequences of underutilization on firms' investment in training is at the core of our analysis, having an accurate measure of the returns from this investment is key. Without an experiment, we would likely target the correlation between the share of trained workers within a firm and sales. However, this correlation would be subject to endogeneity, capturing either heterogeneity in other firm time-invariant characteristics (e.g. TFP), or, if using within firm variation, contemporaneous supply or demand shocks. The wage subsidy experiment generates an exogenous shock to the cost of hiring and training a new worker. Specifically, we estimate the returns to training by targeting the change in sales induced by hiring a new treated worker, where the hiring of such a worker is instrumented by treatment assignment. Similarly, to target non-linearities in workers' labor supply responses to utilization (γ_2), we target the change in the time employees spend at the premises in response to the subsidy.

Table 7 summarizes the estimated parameter values and reports both data and simulated moments. Overall, the table shows a very good fit between the model and the data moments. We further validate the model and estimation by comparing treatment effects in the data and in the simulated model, as explained in the following section.

5.2 Model Validation: Wage Subsidy in the Model vs. Data

To validate the model, we simulate our wage subsidy intervention in the model and compare the implied treatment effects on a range of outcomes with those observed in the data. In the simulation, the wage subsidy is modeled as a cash transfer provided to the firm conditional on hiring an *additional* unskilled worker. Since we did not design a specific training curriculum, we

assume that the firm can freely choose how much training to provide to the new worker (τ^{treat}), and can re-optimize prices and labor utilization in response to the intervention. We consider two versions of the counterfactual: one in which capital is fixed and one in which capital can be adjusted.[13] Workers also choose how much time to spend on the premises in response to the intervention.

The firm problem in the second period, as well as the price optimization, follow the same steps outlined above, with the key difference that the production function is now $y_j = Ak_j^{\alpha}\Big((\phi(\tau_j)b_j + \phi(\tau_j^{treat}))h_j\Big)^{1-\alpha}$.[14] In the first period, firms choose the τ^{treat} and k to maximize:

$$\max_{k_j,\tau_j^{treat}} E_v[p_j y_j - w h_j l_j - \chi_j(\tau_j)b_j - \chi_j(\tau_j^{treat}) - rk_j + WS] \tag{16}$$

where WS denotes the wage subsidy, which, as in the data, is set equal to 65% of the wage.

Table 8 shows the impacts of the intervention in the data and in the simulated model. Specifically, Panel A reports ITT estimates from ANCOVA regressions,[15] as well as LATE estimates from instrumental variable regressions in which the hiring of a trainee is instrumented by treatment assignment. All effects are expressed as percentage changes relative to the control group. Panel B reports analogous changes in firm behavior between the baseline model and the model where firms receive a subsidy to hire a new worker. In the model, firms are homogeneous and therefore there is no heterogeneity in take-up: given the size of the subsidy, it is optimal for all firms to hire an additional worker.

Treatment Effects We begin by describing the effects of the wage subsidy intervention on firm outcomes observed in the data. Given the high take-up rate of the treatment (71%), we focus on ITT effects. These are measured at first follow-up, immediately after the end of the six-month wage subsidy period. Panel A shows that the treatment increased employment by 41% in firms who received the subsidy. This effect is primarily driven by a rise in the number of skilled workers. (28%), indicating that the additional workers hired by treated firms were provided training on the job. We do not find any effect on the value of assets owned or rented by the firm. Among treated firms, sales increased by 24%, with a corresponding, though statistically insignifcant, 5.7% increase in profits.

Despite higher sales, utilization - measured as the number of hours employees spend in produc-

[13]This distinction reflects the possibility that capital adjustment costs prevent firms from varying capital in the short run.

[14]Since tasks are allocated equally across workers and are therefore independent of training, all workers, including the new trainee, optimally choose the same labor supply h.

[15]We run the following ANCOVA regression: $Y_{ibst} = \beta \text{Treat}_i + \alpha_1 Y_{i0} + \alpha_2 \mathbf{X}_{i0} + \gamma_b + \gamma_s + \gamma_t + \varepsilon_{ibst}$. Treat_i is a dummy equal to one for firms assigned to the wage susidy treatment; Y_{i0} and $\mathbf{X}_{i0}$ are, respectively, the value of the outcome and additional control variables (owner's sex, education, firm age, and firm age squared) measured at baseline; γ_b,γ_s and γ_t are branch (location), sector, and survey wave fixed effects, respectively.

tion divided by the number of hours spent at the firm premises - remained unchanged. However, Column 5 shows that total hours spent at the firm premises declined by 10%,[16] suggesting that the wage subsidy had a displacement effect on the intensive margin (lower number of hours) rather than the extensive margin (lower number of employees).

Data vs. Simulated Impacts Panel B compares the observed impacts to those simulated in the model. We focus on the simulation in which capital is fixed. However, the results for outcomes other than assets are very similar when firms are allowed to re-optimize capital. Overall, the magnitude of the simulated effects aligns closely with the experimental estimates. The two outcomes for which the model deviates from the data are hours spent at the firm premises and profits.

The divergence in hours arises because, in the model, labor supply is tightly linked to expected utilization, as shown in equation (15). Both in the data and in the model, utilization declines only modestly in response to the intervention, implying a limited adjustment in labor supply. This muted response helps explain why the model overpredicts the profit impact of the subsidy: higher hours supplied in the model imply lower labor costs relative to the data. In contrast, if firms in the data had to raise wages to induce existing workers to supply time at the firm, profits would increase by less than in the model.

5.3 Counterfactuals

We conduct two sets of counterfactuals. First, we run a quantitative horse race between four key frictions that have been proposed as drivers of the low levels of on-the-job training in low-income countries: training costs (χ), high turnover (γ), high demand volatility (σ_v), and low average levels of demand (μ_v). The first two frictions – training costs and worker separations – have received extensive attention in the literature [Acemoglu and Pischke 1998, 1999, Caicedo *et al.* 2023], which emphasizes the role of upfront investment costs and limited worker retention in shaping firms' incentives to train. By contrast, demand volatility has been largely overlooked as a determinant of training, despite its potential to distort utilization and reduce the returns to fixed training investments. Our first exercise therefore asks whether stabilizing demand, holding its mean fixed, can generate improvements in training and effective labor that are comparable to relaxing these canonical frictions.

Second, we simulate the impact of a battery of supply-side policies – such as our wage subsidy intervention – across environments characterized by different levels of volatility, to assess how policy effectiveness varies with the uncertainty faced by small businesses in low-income countries. This allows us to evaluate whether demand stabilization can amplify policy effectiveness by

[16]The reduction in the number of hours is similar among pre-existing employees and the worker hired through the subsidy.

increasing the returns of investing in inputs that require upfront investments.

Determinants of Training We quantitatively assess the relative importance of different channels in driving the low levels of training observed in low-income countries. To do that, we construct counterfactual scenarios where we change the magnitude of each of the model parameters of interest - χ, γ, σ_v, and μ_v - to induce a 10% increase in sales. We the compare the resulting effects on the number of workers, utilization, time spent by workers on the firm premises, training, as well as a composite measure of effective labor that incorporates all of these margins.

The results are shown in Figure 5. Panel A shows the relative changes in the model parameters necessary to induce a 10% rise in revenues. It shows that the same revenue increase can be achieved by lowering training costs or workers' outside option by approximately 5%, increasing the mean of the demand shock by 8.8%, or reducing volatility by 0.6%. This first set of results already points to the quantitative importance of demand volatility: a very small reduction in volatility is sufficient to generate the same revenue gains as substantially lowering canonical training frictions.

Panel B shows the effects on the various components of labor. The first component is the number of workers employed by the firm. The results show that all parameter changes induce firms to hire more workers, as they either decrease the cost or increase the returns from having additional employees. Reductions in training costs and demand volatility, as well as increases in demand levels, have the largest effects on employment - respectively 10.4%, 9.1%, and 9.5%. A reduction in workers' outside option only leads to a 5.3% increase in employment. This is because, in response to a lower outside option, workers spend almost 5% more time at the firm premises, while the other parameters have negligible effects on this margin. As a result, a smaller increase in headcount is sufficient to generate comparable increases in total labor supply.

Utilization is also largely unaffected by the parameter changes. While this is what we would expect for training costs and the outside option, the result may be more surprising for the demand-volatility counterfactual. However, the reason we observe only a small increase in utilization is that σ_v needs to fall by just 0.6% to generate a 10% increase in sales. Because of its limited effect on utilization, lower demand volatility increases the share of trained workers by only 0.4%. Lower training costs and a lower outside option have larger effects, leading to a 2% increase in the share of trained workers.

Panel C shows results on the the overall number of trained workers and on effective labor, calculated as the product of the number of workers, utilization, time spent at the premises, and returns to training ($\phi(\tau)$).[17] Overall, the figure shows that a reduction in training costs has the largest effect on the number of trained workers (12.7%), followed by an increase in demand levels and a decrease in volatility (9.7% and 9.5%, respectively). This result is quite striking, as it implies that reducing demand *volatility* (while holding the *mean* fixed) raises the number of trained workers by almost as much as lowering training costs, a channel that has traditionally

[17]The results are very similar when using the share of trained workers τ.

received far more attention in the literature. Decreasing workers' outside option has the smallest impact on the number of trained workers (7.5%), as it incentivizes firms to provide training to a smaller number of workers who supply more time, rather than expanding their workforce.

From the firm's perspective reductions in training costs and the outside option generate the largest increases in effective labor (12.1%). However, the effects induced by changes in demand volatility and demand levels are only slightly lower (10.4% and 10.2%, respectively). Importantly, this implies that stabilizing demand – without increasing its average level – can deliver gains in effective labor that are nearly as large as those obtained by directly reducing training costs or turnover frictions. In other words, demand volatility itself is a quantitatively important determinant of training and effective labor, alongside the canonical mechanisms emphasized in the literature.

Wage Subsidy Effectiveness We examine how the effectiveness of wage subsidies varies across environments. Specifically, we compare the baseline impact of our intervention to its impact under lower training costs, lower worker outside options, lower demand volatility, and higher demand levels, using parameter changes that generate a 10% increase in firm revenues. The results are shown in Figure 6.

Panel A shows that wage subsidies are most effective at increasing the number of trained workers and effective labor when training costs are low, with gains 9.3% and 9.2% larger than in the baseline, respectively. Lower demand volatility and higher demand also increase effectiveness, though to a lesser extent (5% and 6%). In contrast, a lower worker outside option reduces the impact on the number of trained workers (3.2%), as the additional worker hired through the subsidy induces a smaller reduction in incumbent hours, lowering firms' incentives to train the new worker.

Panel B shows that displacement effects are key for firm outcomes. When workers have a lower outside option, wage subsidies generate 4.5% larger increases in revenues and profits. Lower training costs play a more modest role for firm outcomes (1.9% and 3.1%), while lower demand volatility leads to increases of 2.4% and 3% in revenues and profits, respectively, relative to the baseline scenario.

We test these predictions in the data by examining heterogeneity in the effects of the wage subsidy by baseline demand volatility. To do so, we calculate the coefficient of variation in monthly profits at baseline and classify firms as facing high uncertainty if their coefficient of variation is above the median. The results, shown in Table 9, are in line with the model's predictions. Firms with higher profit volatility provide less training and exhibit larger reductions in labor supply in response to the subsidy, with weaker (though not statistically different) effects on sales and revenues.

Overall, these results show that demand uncertainty – a margin that has so far been largely overlooked – plays an important role in shaping policy effectiveness. We explore this further

by simulating standard supply-side policies across environments with different levels of demand volatility.

Volatility and Policy Effectiveness Figure 7 reports results from model simulations of four counterfactual policies: training cost reductions (Panel A), capital rental cost reductions (Panel B), improved market access (Panel C), and management training (Panel D). These are simulated through changes in χ, r, μ_v, and A that generate a 10% increase in revenues in the baseline scenario. We simulate these policies under three environments characterized by different levels of demand volatility: baseline (in yellow), 5% lower volatility relative to baseline (in blue), and 5% higher volatility relative to baseline (in green). For each of these environments, the graphs show changes in the number of workers, capital, profits and training induced by the policy.

The results clearly show that policy effectiveness is mediated by the volatility of demand firms face in the environment in which they operate. A 5% decrease in demand volatility more than doubles the impact of all policies on labor, capital, and profits. Conversely, a 5% increase in volatility leads to effects that are roughly half the size of those in the baseline scenario. This pattern is consistent across all interventions and reflects a common mechanism: lower volatility raises expected utilization, thereby increasing the returns to expanding capacity through hiring and capital accumulation. In contrast, when volatility is high, firms anticipate that a larger share of inputs will remain idle, which dampens their response to policies that operate through these margins.

The figure also highlights that the magnitude of this amplification effect is similar across different types of interventions. Policies that act directly on costs (such as reductions in χ or r) and those that increase demand or productivity (through μ_v or A) all exhibit substantially larger effects in low-volatility environments. This suggests that demand stabilization does not only shift outcomes directly, as highlighted in the first counterfactual, but also increases the responsiveness of firms to a broad class of supply-side policies.

6 Conclusions

This paper studies the causes and consequences of labor underutilization in small and medium-sized firms in Uganda. We document four central facts. First, firms face substantial and difficult-to-predict demand volatility. Second, capital and labor adjustment costs are significant, limiting firms' ability to respond to shocks along extensive margins. Third, labor underutilization is pervasive, with workers spending a large fraction of their time idle. Fourth, firms with more volatile demand exhibit lower utilization and invest less in training.

Guided by these facts, we develop and estimate a model of firm input and training choices under demand uncertainty and adjustment costs. A key mechanism is that training requires upfront fixed investment, while workers are largely compensated on a piece-rate basis. Higher demand volatility

lowers expected utilization and therefore reduces the returns to fixed training investments, generating a novel demand-side channel through which uncertainty depresses firm-sponsored human capital accumulation. We validate the model by showing that simulated treatment effects of a wage subsidy intervention closely track the experimental estimates.

Our counterfactual analysis yields two main insights. First, reducing demand volatility increases hiring and training by nearly as much as directly lowering training costs or worker separations. Demand stabilization policies can therefore be as powerful as traditional supply-side interventions aimed at stimulating skill investment. Second, the effectiveness of commonly studied development policies to stimulate firm productivity and growth—including wage subsidies, capital grants, improved market access, and management training—depends critically on the level of demand volatility. These interventions generate substantially larger impacts when firms operate in more stable environments.

This second finding is perhaps the most important contribution of our paper. A large experimental literature has evaluated firm-targeted interventions in developing countries, often finding impacts that are positive but modest and sometimes short-lived. Our results suggest a new interpretation of this mixed evidence: the returns to these interventions are not fixed structural parameters but are substantially mediated by the demand environment in which firms operate. Firms facing high demand volatility optimally keep resources underutilized, which limits their ability to benefit from any intervention that increases input availability or quality.

Taken together, our findings highlight the importance of demand-side frictions [Goldberg and Reed 2023] in shaping firm dynamics and human capital accumulation in low-income settings. Policies that reduce demand uncertainty—through improved market integration, demand stabilization, or better market information—may therefore be a crucial complement to conventional supply-side interventions, and their absence may help explain why the latter have so often disappointed. Understanding how to design and combine such policies to unlock firm growth and human capital accumulation in low-income settings remains an important avenue for future research.

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Table 1: Firm Descriptives at Baseline

Sample: All firms at baseline

Means, standard deviations of continuous variables in parentheses

	Mean or Percentage	Standard Deviation
A. Firm and Owner Characteristics		
Age of firm	6.42	(4 54)
Monthly profits	218	(329)
Gender of owner (female)	53 8	
Age of owner	34 2	(7 30)
Manufacturing	38 10	
Welding (14.8%), Motor mechanics (9.5%), Electrical (6.0%), Construction (4.6%), Plumbing (3.2%)		
Services	61.9	
Hairdressing (39.7%), Tailoring (14.9%), Catering (7.3%)		
B. Capital and Labor		
Value of capital stock	1256	(2361)
Capital per worker	481	(994)
Number of employees	2.96	(2 31)
Share workers with other firms	8.78	
Share machines with other firms	23 0	
C. Training (worker specific)		
Share of employees that are skilled	72 1	
Share of skilled employees that were trained by the firm	32 2	
Number of current trainees	.400	(1 16)

Notes. All the variables in panels A, B, and C are at the firms level and collected at baseline. The variables in panel D is at the worker level and collected at follow-up 1, from a panel of all the workers employed by the firms at the time of the interview. The top 1% observations in the profits and capital stock variables are excluded from any analysis involving the corresponding variables. Currently borrowing is a dummy equal to 1 if the owner is borrowing at the time of the interview. All monetary amounts are deflated and expressed in terms of the price level in January 2013 using the monthly Producer Price Index for the manufacturing sector (local market), published by the Uganda Bureau of Statistics. The monetary amounts are then converted in January 2013 USD.

Table 2: Worker Descriptives at Baseline

Sample: Worker roster from control firms at first follow-up

Means, standard deviations of continuous variables in parentheses

	Mean or Percentage (1)	Standard Deviation (2)
A. Skills and Experience		
Received on-the-job training (at the firm)	49 7	
Completed vocational training	26 9	
B. Compensation		
Full time	95.3	
Paid piece rate (along with salary or in-kind)	66.8	
Paid piece rate only	49.1	
C. Tenure, Hours and Earnings		
Tenure at the firm (months)	19.2	(23 1)
Hours worked per day	11.0	(2 15)
Total hours worked per month	280 2	(70 1)
Total earnings last month	60 4	(52 5)

Notes: All data comes from the employee roster for control firms during the 1st follow-up. The table reports mean outcomes and standard deviation in parentheses. In Panel B the *'paid piece rate'* dummy equals one if the employee is usually paid a piece-rate (along with any other form of payment – including a base salary or in-kind payment). In Panel C, the *total hours worked per month* is calculated by multiplying hours worked per day by days worked per week, and multiplying by four. *Total earnings in the last month* includes both money and in-kind payments made to the employee. All monetary variables (earnings and prices) are winsorized at the top 1% (in-kind and money earnings and winsorized separately before they are summed for total earnings) and deflated at August 2012 prices, using the monthly consumer price index published by the Uganda Bureau of Statistics. Deflated monetary amounts are then converted into August 2012 USD.

Table 3: Demand Uncertainty

Sample: Control firms at first follow-up (A) and all follow-ups monthly panel (B, C)
Means, standard deviations in parentheses

	Min	Max	Expected Value	Standard Deviation	Coefficient of Variation	Firm Fixed Effects (i)	Month x Sector Fixed Effects (ts)	Unexplained Variation (its)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Demand Uncertainty (Cross Section)								
Expected monthly revenues, next six months	248	833	467	125	239			
	(327)	(1179)	(581)	(207)	(.104)			
Expected customers, next seven days	11 3	34 1	21.0	4.50	219			
	(28.2)	(69.4)	(22.9)	(5.48)	(.097)			
B. Realized Demand (Panel)								
Actual monthly revenues	-2614	6065	581	608	1 05	41.5%	3.46%	55.0%
C. Realized Inputs (Panel)								
Value of capital stock	-2840	5247	1227	238	194	98.1%	1.31%	0.59%
Number of employees	-2 94	10 1	2 44	1 29	528	64.0%	7.57%	28.4%

Note: Panel A uses data from the Control group at first follow-up. Each firm owner was asked the following questions: (1) Imagine that over the next 6 months the revenues from this business are very high. What is the maximum amount of revenues the ownercould make in the best month over the next 6 months? (2) Imagine that over the next 6 months the revenues from this business are very low. What is the minimum amount of revenues the owner could make in the worst month over the next 6 months? (3) In how many months over the next 6 months, does the owner think that the monthly revenues from this business' activities will be higher than (max-min)/2? We use these three questions to recover the owner's distribution of expectations, assuming a triangular distribution (Attanasio and Kaufmann, 2014). We follow the same approach for epectations regarding the number of customers, which are measured over a seven days period. Panel B uses monthly data from the Control group at all follow-ups to show the variation in revenues, number of workers and value of capital that is predicted by month-sector fixed effects, net of firm fixed effects. It captures predictable time variation driven by seasonality. In Column (6), the Between Adjusted R-squared is the variation explained by firm fixed effects. In Column (7), the Within Adjusted R-squared is the variation explained by interview month fixed effects.

Table 4: Input Responsiveness to Demand Shocks

Sample: All firms at all follow-ups - monthly and follow-up panels
IV regression coefficients, robust standard errors in parentheses

	Log (Total Value of Assets)	Log (Number of Employees)	Log (Total Value of Assets)	Log (Number of Employees)	Log(Labor Utilization)	Log(Hours at the premises)	Log(Hours in production)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log (Revenues)	.004	-.003	0.148**	-.018	.830***	-0.032	0.734**
	(.008)	(.016)	(0.066)	(.090)	(.368)	(0.073)	(0.327)
First stage coefficients:							
Mean log(revenues), other firms	.508***	.504***	.284***	.277***	.277***	.277***	.277***
	(.020)	(.019)	(.069)	(.068)	(.068)	(.068)	(.068)
First stage F-stat	171	170	4.58	4.37	4.37	4 37	4 37
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean outcome for control firms	6 55	1 05	6.765	1 30	-1 77	5.569	3.870
Number of observations	7 743	7 847	1275	1 296	1 296	1 296	1 296

Notes: The dataset used is a monthly panel of firms in Columns 1 and 2 and a panel of firms at follow-up level restricted to the sample for which labor utilization information is available in Columns 3 to 7. For each firm, monthly revenues are instrumented by the average value of monthly revenues among firms in the same sector, branch, and month, excluding the firm itself. All regressions include firm fixed effects. *Labor utilization* is measured as the number of monthly hours actually worked over the number of monthly hours the worker spent at the firm premises. Mothly hours at firm premises are computed multipling the average number of hours by the number of days the worker report being at the firm in a typical day. Monthly hours actually worked is calculated as follows. For each workers paid piece-rate, we ask the following three questions regarding a specific product/service: (1) How much time (minutes) would <name> normally take right now to complete his/her work on this product/service alone to a standard of quality considered satisfactory by the average customer of this business? (2) How much of the price charged to customers for this product/service does <name> normally receive? In addition, we have data on the total earnings of the worker in the month prior to the survey. We calculate the number of products/services the worker has worked on in the last month by dividing total earnings by the piece-rate. We then calculate monthly hours actually worked as the number of products/services the workers has worked on in the last month times the average time taken to complete the product/services. Monthly hours worked can only be calculatd available from second follow-up and for workers paid per-piece (68% of all workers). ***denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 5: Training Costs

Sample: Worker roster from control firms at first follow-up
Means, standard deviations of continuous variables in parentheses

	Mean or Percentage (1)	Standard Deviation (2)
A. Labor costs of training		
Trainee was unpaid	51 5	
Trainee was paying the owner	28 8	
Trainee was paid	19 7	
B. Time costs of training		
Length of training (months)	9 06	(4.89)
Mainly conducted by owner	45 6	
Conducted by owner and co-workers	45 1	
Conducted by co-workers only	9 07	
Hours owner spent at the premises last month	291	(60.1)
Hours spent training in the last month	50 3	(87.8)
Hours spent training in the last month | Training	113	(101)
C. Tools/material costs of training		
Any such cost	82 7	
Owner paid most costs | any such costs	55 9	
Employee paid most costs | any such costs	36 2	
Owner-employee share costs | any such costs	7 90	

Notes: All data comes from the employee roster for control firms during the 1st follow-up. The table reports mean outcomes, with standard deviation in parentheses. The monthly number of hours the owner spends at the firm is calculated assuming owners spend 6 days a week at the firm. All monetary variables (earnings and prices) are winsorized at the top 1% (in-kind and money earnings and winsorized separately before they are summed for total earnings) and deflated at August 2012 prices, using the monthly consumer price index published by the Uganda Bureau of Statistics. Deflated monetary amounts are then converted into August 2012 USD.

Table 6: Uncertainty, Utilization, and Training

Sample: Workers panel first follow-up all firms (col 1) nd firm panel first follow-up (col 6) and all follow-ups (other cols)
OLS regression coefficients, robust standard errors in parentheses

	Labor Utilization					Hours spent Training in the Last Month (Owner)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PANEL A: Uncertainty								
Coefficient of Variation, *Expected* Monthly Revenues	-.262***					-174.0***		
	(.086)					(38.56)		
Coefficient of Variation, *Current* Monthly Revenues		-.076	-.529***				3.083	-60.99*
		(.048)	(.166)				(8.902)	(35.86)
PANEL B: Adjustment Costs								
Residual K/L Ratio				.010***	.028***			
				(.002)	(.006)			
First Stage Coefficients:			.548***					0.451***
Mean CV of monthly revenues, other firms			(.068)					0 045
Mean Outcome for Controls	.120	.277	.279	.305	.305	66.195	50.969	51.470
Survey wave fixed effects	-	No	No	Yes	No	-	No	No
Sector and location fixed effects	Yes	No	No	Yes	No	Yes	No	No
Firm fixed effects	No	Yes	Yes	No	Yes	No	Yes	Yes
Number of observations	527	1316	1287	1428	1428	575	2411	2331

Notes: The table shows the results from a regression of labor utilization and number of hours the firm owner spent trining workers in the month prior to the survey on the coefficient of variation of expected and current monthly revenues. The unit of observation is the employee in Column 1 and 6, and the firm in Columns 2 to 5 and 7 to 8. The coefficient of variation of expected monthly revenues is only measured at first follow-up, and so the sample in Columns 1 and 6 only includes firms at first follow-up. In Columns 3, and 8, for each firm, the coefficient of variation of firms' monthly revenues is instrumented by the average coefficient of variation of monthly revenues among firms in the same sector, branch, and survey round excluding the firm itself. *Labor utilization* is measured as the number of monthly hours actually worked over the number of monthly hours the worker spent at the firm premises. Mothly hours at firm premises are computed multipling the average number of hours by the number of days the worker report being at the firm in a typical day. Monthly hours actually worked is calculated as follows. For each workers paid piece-rate, we ask the following three questions regarding a specific product/service: (1) How much time (minutes) would <name> normally take right now to complete his/her work on this product/service alone to a standard of quality considered satisfactory by the average customer of this business? (2) How much of the price charged to customers for this product/service does <name> normally receive? In addition, we have data on the total earnings of the worker in the month prior to the survey. We calculate the number of products/services the worker has worked on in the last month by dividing total earnings by the piece-rate. We then calculate monthly hours actually worked as the number of products/services the workers has worked on in the last month times the average time taken to complete the product/services. Monthly hours worked can only be calculatd available from second follow-up and for workers paid per-piece (68% of all workers). The *Coefficient of variation of the firm's expected revenues* is calculated as follows. Each firm owner was asked the following questions: (1) Imagine that over the next 6 months the revenues from this business are very high. What is the maximum amount of revenues the ownercould make in the best month over the next 6 months? (2) Imagine that over the next 6 months the revenues from this business are very low. What is the minimum amount of revenues the owner could make in the worst month over the next 6 months? (3) In how many months over the next 6 months, does the owner think that the monthly revenues from this business' activities will be higher than (max-min)/2? We use these three questions to recover the owner's distribution of expectations, assuming a triangular distribution (Attanasio and Kaufmann, 2014). ***denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 7: Parameter Estimates and Model Fit

Parameter	Value	Targeted Moment	Data
Estimated			
Cross-section:			
α	0.327	Labor share	0.329
θ	8.366	Average markup	2.700
χ	1.374	Share of trained workers	0.497
σ_v	3.563	Labor utilization	0.569
γ_1	1.517	Time supplied by workers	0.442
w	2.056	Number of workers	2.946
A	12.053	Number of machines	2.306
Experiment:			
ϕ	0.882	LATE on firm revenues	0.319
γ_2	2.104	Time supplied — treatment	0.397
Calibrated			
r	0.514	Hourly rent (Bassi et al. 2022)	0.514

Table 8: Treatment Effects, Model vs. Data
% changes, All firms at Follow-up 1

	Number of Workers	Number of Skilled Workers	Total Value of Assets	Utilization	Time at the Firm Premises	Sales	Profits
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A: Data							
Intention To Treat (ITT)	.412***	.281***	.003	-.081	-0.091**	.238*	.057
	(.077)	(.092)	(.037)	(.205)	(0.035)	(.130)	(.108)
Local Average Treatment Effect (LATE)	.539***	.477***	.037	-.088	-0.112***	.319**	.100
	(.117)	(.122)	(.106)	(.268)	(0.038)	(.155)	(.133)
PANEL B: Model							
Simulated Treatment Effect (K Fixed)	.339	.382	.000	-.031	-.033	.179	.136
Simulated Treatment Effect (K Variable)	.339	.382	.179	-.031	-.033	.273	.226

Notes: The table shows treatment effects for the wage subsidy intervention in the data (Panel A) and the model (Panel B). Effects are expressed as percentage changes relative to the control group. In Panel A, Local Average Treatment Effects are estimated instrumenting the take-up of the Wage Subsidy intervention with assigment. Panel B shows results from two separate simulations of the Wage Subsidy intervention in the mode: one where we hold capital to the same level as control group (K fixed), and one in which we allow firms to reoptimize capital (K variable).

Table 9: ITT on Firm and Worker Characteristics, by CV of baseline expected profits

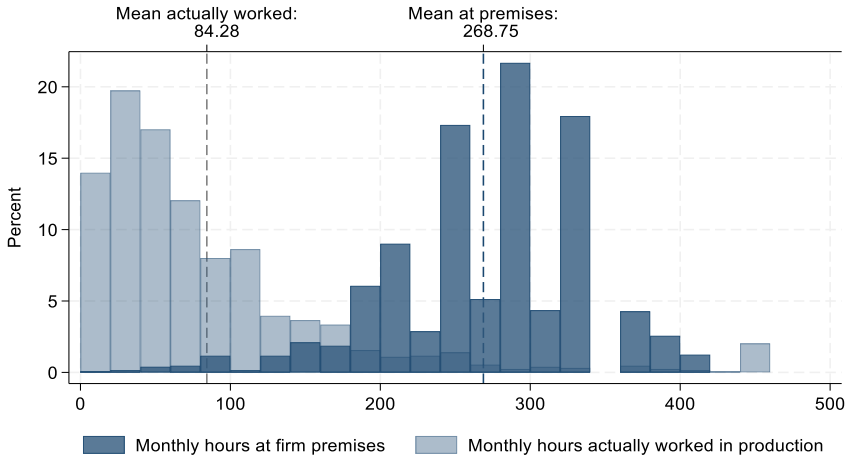
	Treated workers	All workers					
	Training	Utilization	Hours at the firm (Log)	Hours in production (Log)	Total Value of Assets	Sales (log)	Profits (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wage Subsidy	.414***	.007	-.007	-0.069	0.045	0.201	0.049
	(.067)	(.032)	(.048)	(0.406)	(0.060)	(0.138)	(0.121)
Wage Subsidy X High Uncertanty	-.175*	.005	-.124*	-0.274	-0.086	-0.111	-0.220
	(.097)	(.076)	(.068)	(0.682)	(0.078)	(0.236)	(0.244)
High Uncertainty	.092	.034	-.004	0.414	0.022	-0.041	-0.013
	(.100)	(.044)	(.042)	(0.333)	(0.044)	(0.124)	(0.131)
Mean of outcome in control	.583	.292	5.563	3.796	6.451	5.681	4.968
Num of firms	261	192	442	190	539	591	535
Num of observations	285	446	1330	432	539	591	535

Notes: The table reports the results from a regression on workers characteristics at follow-up 1 ("short-term"). The sample includes treatment workers hired through the wage subsidy and the first worker hired by firms in the Control group in Column 1, all workers in Columns 2 and 3, and all firms in Columns 5 to 7. All regressions controls for owner's sex and education, business' age and quadratic business' age. Regression also include location (branch), trade, follow-up and interview month fixed effects. The observations are weighted for the probability to appear in the panel at each follow-up. The errors are clustered at the branch-trade level. High uncertainty is a dummy indicating the firm is over the sector-specific median of coefficient of variation of monthly expected profits at baseline. The observations are weighted for the probability to appear in the panel at each follow-up. The errors are clustered at the branch-trade level. High uncertainty is a dummy indicating the firm is over the sector-specific median of coefficient of variation of monthly expected profits at baseline. The top 1% of number of workers, value asset, sales, and profit is trimmed. Labor utilization is measured as the number of monthly hours actually worked over the number of monthly hours the worker spent at the firm premises. Mothly hours at firm premises are computed multipling the average number of hours by the number of days the worker report being at the firm in a typical day. Monthly hours actually worked is calculated as follows. For each workers paid piece-rate, we ask the following three questions regarding a specific product/service: (1) How much time (minutes) would <name> normally take right now to complete his/her work on this product/service alone to a standard of quality considered satisfactory by the average customer of this business? (2) How much of the price charged to customers for this product/service does <name> normally receive? In addition, we have data on the total earnings of the worker in the month prior to the survey. We calculate the number of products/services the worker has worked on in the last month by dividing total earnings by the piece-rate. We then calculate monthly hours actually worked as the number of products/services the workers has worked on in the last month times the average time taken to complete the product/services. Monthly hours worked can only be calculatd available from second follow-up and for workers paid per-piece (68% of all workers).***denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

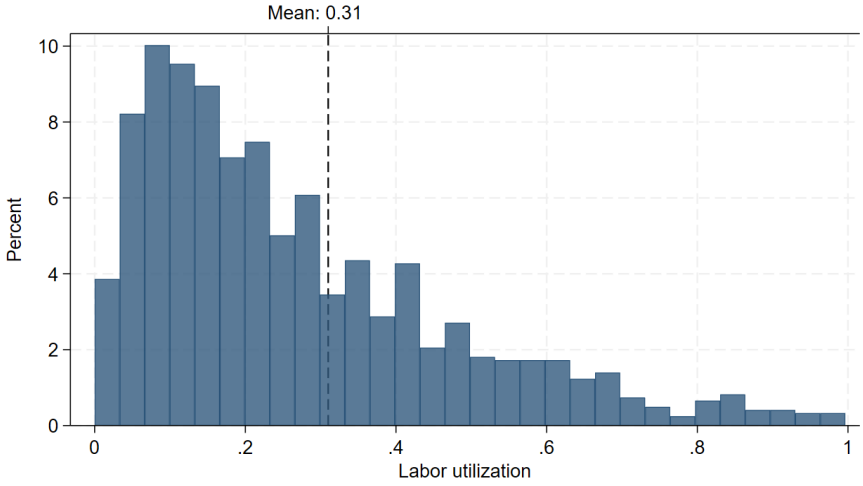
Figure 1: Labor Utilization

Sample: Worker panel control firms 2-3-4 follow-ups

A: Hours Worked and Hours at Business Premises

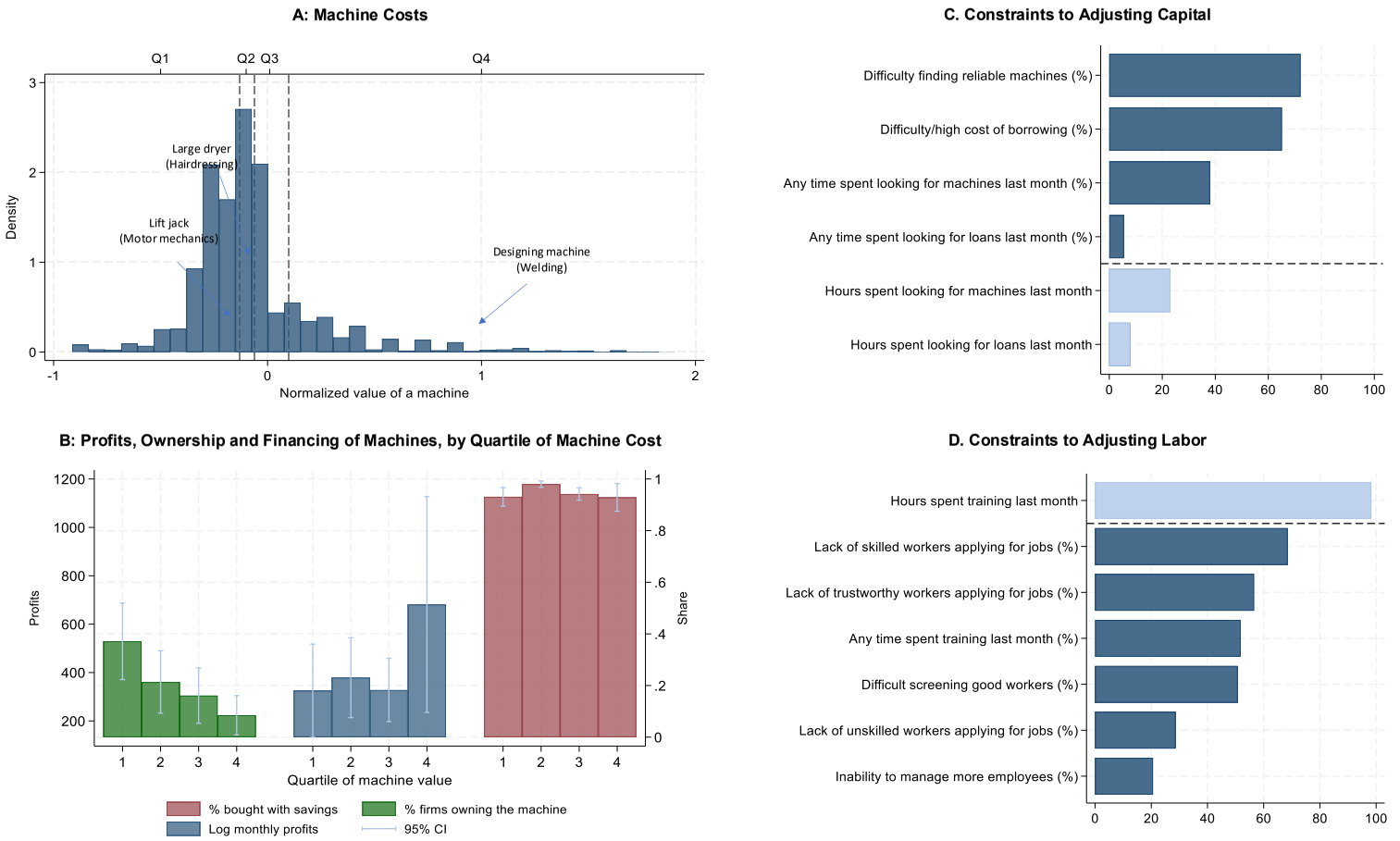


B: Labor Utilization Rate



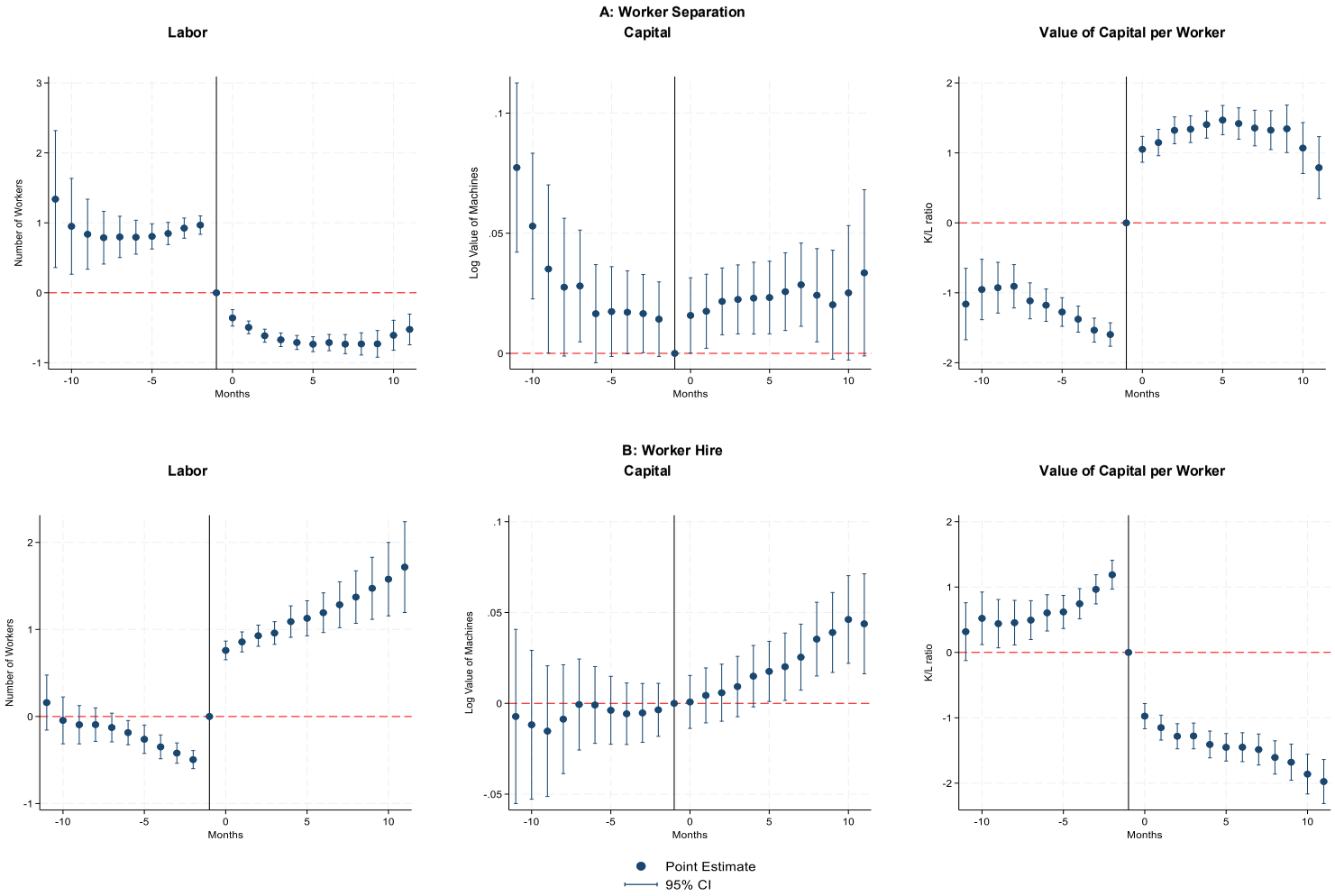
Note: The figures uses worker-level data from the Control group at second, third and fourth follow-ups. Panel A shows the distribution of the monthly number of hours workers typically spend at the firm (in dark blue) and the monthly number of hours actually worked in production (in light blue). Hours actually worked is calculated as follows. For each workers paid piece-rate, we ask the following three questions regarding a specific product/service: (1) How much time (minutes) would <name> normally take right now to complete his/her work on this product/service alone to a standard of quality considered satisfactory by the average customer of this business? (2) How much of the price charged to customers for this product/service does <name> normally receive? In addition, we have data on the total earnings of the worker in the month prior to the survey. We calculate the number of products/services the worker has worked on in the last month by dividing total earnings by the piece-rate. We then calculate monthly hours actually worked as the number of products/services the workers has worked on in the last month times the average time taken to complete the product/services, which therefore only reflects the hours spent on production. Panel B shows the labor utilization, computed as percentage of hours in the premises spent in productive activities.

Figure 2: Machines and Perceived Constraints to Adjusting Inputs



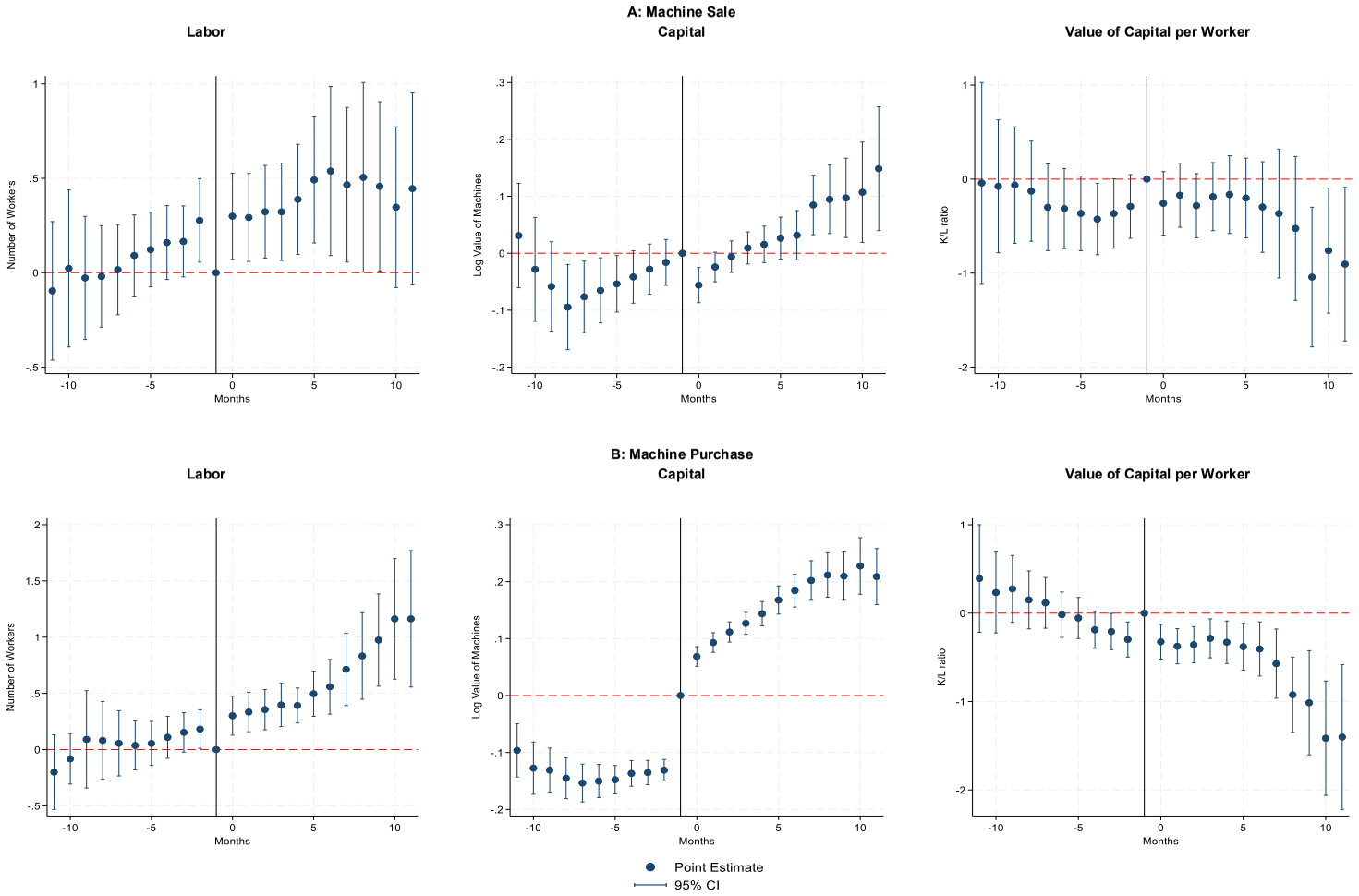
Notes: Panel A plots the distribution of machine values at baseline. The unit of observation is a specific machine owned by a given firm. Machine values are normalized by the mean and standard deviation of machine values in the sector in which the firm operates. In Panel B, we first calculate the average (normalized) value of a given machine type (e.g. lift jacks) across all firms who have access to that machine. We then rank the machines according to their average value and assign them to quartiles. Finally, we calculate average profits, share of ownership and share of machies boughts with savings/reinvested profits among firms who own a machine in a given quartile of the machine value distribution. The dotted lines in Panel A indicate the thresholds corresponding to the quartiles of machine values used in Panel B. Panel C and D use data from all firms at first follow-up (time variables) and at baseline (difficulties with machines and workers). All variables refer to month prior the interview. The number of hours spent training, looking for machines and looking for loans in the last month are conditional on the owner having spent at least one day training, looking for machines or looking for loans in the last month.

Figure 3: Worker Separation and Hire Event Studies



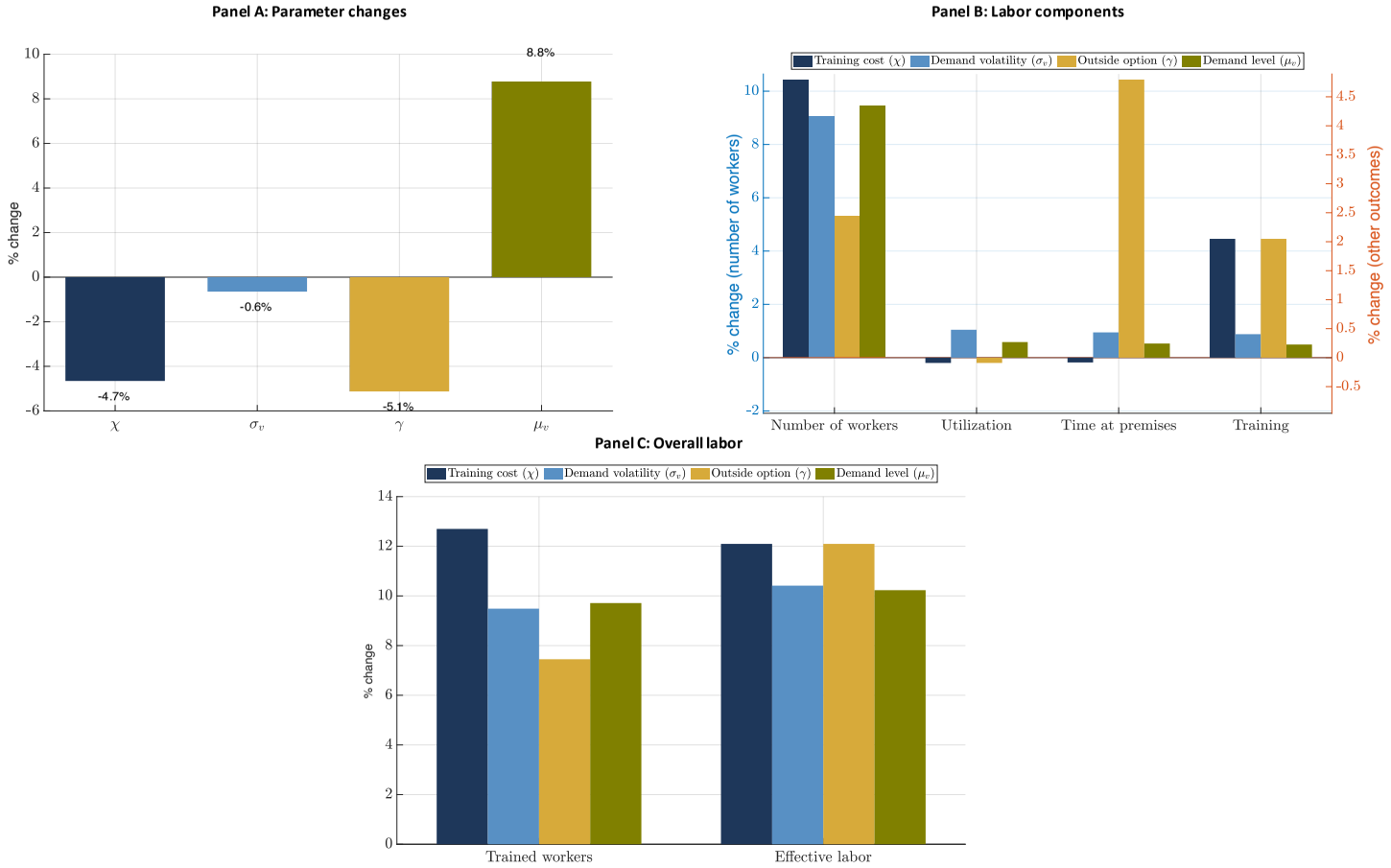
Notes: These figures show event studies for the hiring of a new worker (Panel A), the firing or loss of a worker (Panel B), the purchase of a new machine (Panel C), the loss of a worker for reasons that did not depend on the owner (e.g., the worker left or died) (Panel D). The event is the hiring of a new worker (Panel A), and the firing or loss of a worker (Panel B), the purchase of a new machine (Panel C), and the non-volutnary loss of a worker (Panel D) in the 12 month before a given follow-up survey. The graphs show the results of the analysis pooled across all follow-ups. The outcomes are the logarithm of the firm's total value of assets over the number of workers employed at the firm, including the firm owner (K/L ratio), the number of workers employed at the firm, including the firm owner (Labor) and the logarithm of the firm's total value of assets (Capital).

Figure 4: Machine Sale and Purchase Event Studies



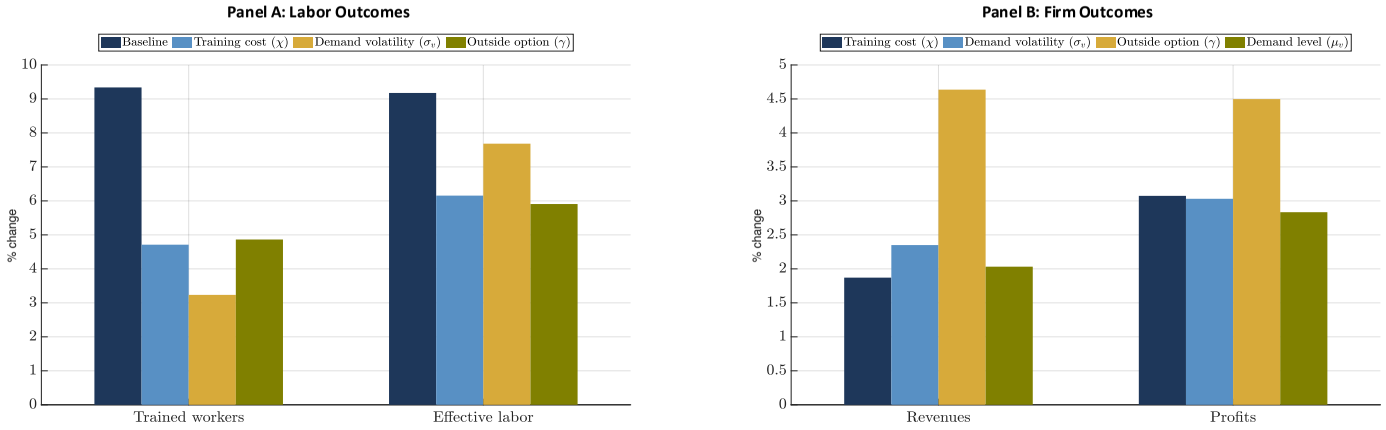
Notes: These figures show event studies for the hiring of a new worker (Panel A), the firing or loss of a worker (Panel B), the purchase of a new machine (Panel C), the loss of a worker for reasons that did not depend on the owner (e.g., the worker left or died) (Panel D). The event is the hiring of a new worker (Panel A), and the firing or loss of a worker (Panel B), the purchase of a new machine (Panel C), and the non-volutnary loss of a worker (Panel D) in the 12 month before a given follow-up survey. The graphs show the results of the analysis pooled across all follow-ups. The outcomes are the logarithm of the firm's total value of assets over the number of workers employed at the firm, including the firm owner (K/L ratio), the number of workers employed at the firm, including the firm owner (Labor) and the logarithm of the firm's total value of assets (Capital).

Figure 5: Counterfactual, Training Frictions - 10% increase in sales



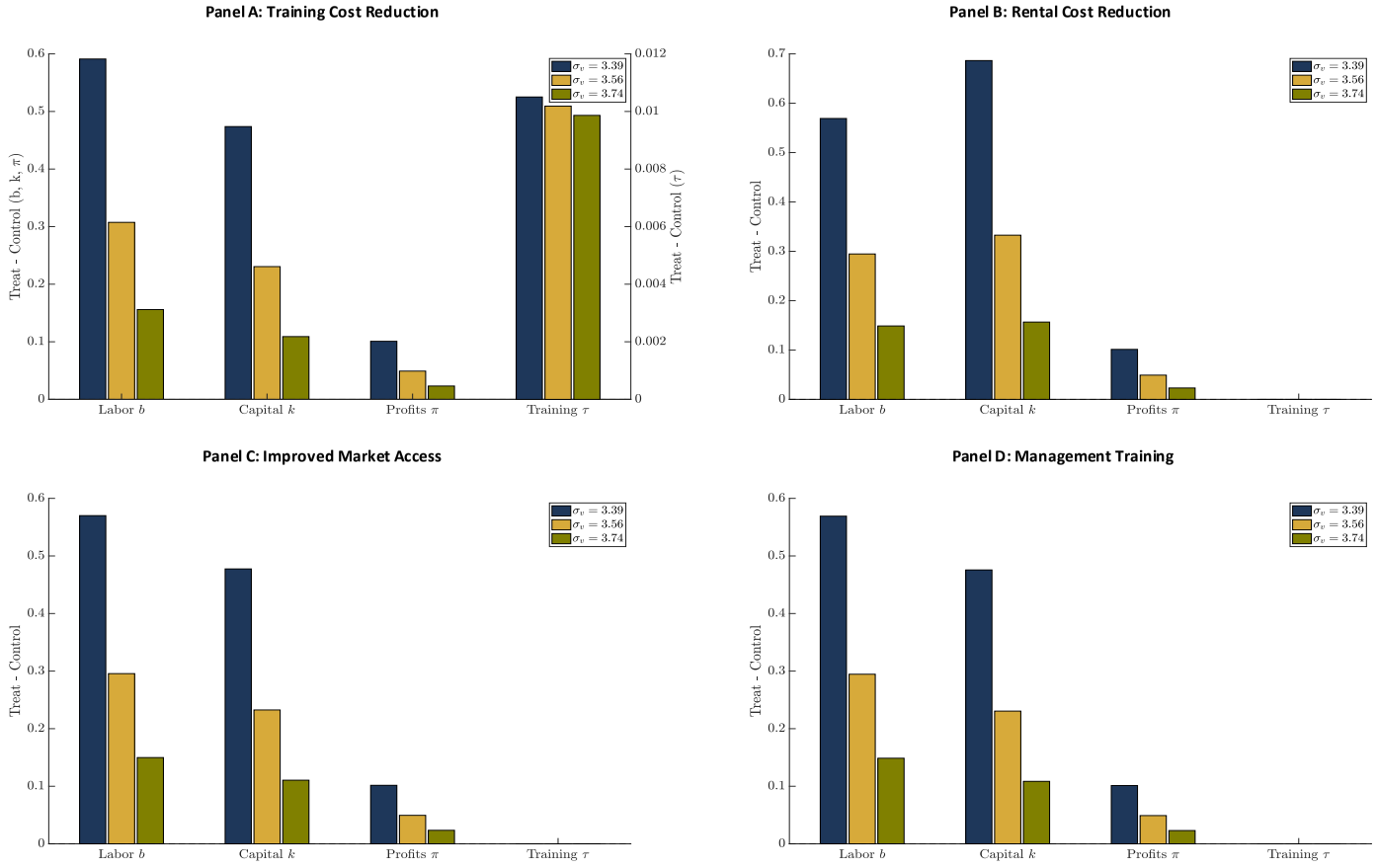
Notes: Figure 5 shows changes in worker and firm outcomes relative to the baseline estimation in counterfactual simulations where we change each parameter (chi, sigma, gamma, and mu) to induce a 10% increase in firm sales. Panel A shows the magnitude of the parameter changes needed to induce such increase in sales.

Figure 6: Counterfactual Effects of Wage Subsidy



Notes: Figure 6 simulates shows percentage changes in the wage subsidy treatment effects in environments with lower training costs, demand volatility, worker outside option, and higher demand level. Changes in parameters are calibrated to generate a 10% increase in firm revenues in the baseline scenario with no wage subsidy. Effective labor is the product of number of workers, returns to training (given the training level chosen by the firm), hours spent at the premises, and utilization.

Figure 7: Counterfactual Effects of Policies under Uncertainty



Notes: Figure 7b simulates different types of policy interventions across firms facing heterogeneous levels of demand uncertainty (sigma_v). In all panels, the blue line show outcomes for firms in the Control group, namely firms with baseline values of the model parameters (apart from sigma_v, which changes along the x-axis). In Panel A, the Treatment line shows outcomes for firms facing 20% lower training costs (chi). In Panel B, it shows outcomes for firms facing 20% lower rental prices (r). In Panel C, it shows outcomes for firms facving a 20% higher mean demand level. In Panel D, it shows outcomes for firms with a 20% higher TFP (A).

Appendix 1: Additional Tables and Figures

Table A1: Attrition

OLS regression coefficients, robust standard errors in parentheses, and F-tests in brackets

Dependent Variable: Firm attrited or closed in each follow-up

Attrited by:	1st follow-up	2nd follow-up	3rd follow-up	4th follow-up
	(1)	(2)	(3)	(4)
Monthly profits (log)	-.042**	-.013	-.006	-.014
	(.017)	(.016)	(.017)	(.021)
Number of employees	-.013**	-.014**	-.012**	-.016**
	(.006)	(.006)	(.006)	(.008)
Number of unskilled employees	.018*	.014	.008	.001
	(.010)	(.009)	(.009)	(.011)
Capital stock (log)	.010	-.007	.001	.003
	(.011)	(.011)	(.012)	(.014)
Firm's age	-.004	-.005*	-.009***	-.014***
	(.003)	(.003)	(.003)	(.003)
Attrition Rate	.160	.181	.186	.322
Owner and firm characteristics	Yes	Yes	Yes	Yes
Sector and branch fixed effects	Yes	Yes	Yes	Yes
F-test on firm characteristics	[.005]	[.040]	[.007]	[.000]
F-test on owner characteristics	[.678]	[.414]	[.200]	[.623]
Number of observations	1,025	1,025	1,025	1,025

Notes: Standard errors are adjusted for heteroskedasticity in all regressions. The two stratification variables used for the randomisation of firms at baseline are: trade and BRAC branch. All regressions include trade and branch fixed effects. Firms that were found shut-down were not interviewed and are here considered attriting. All covariates are measured at baseline. The top 1% of profit and capital values are excluded. All monetary variables are deflated and expressed in terms of August 2012 prices, using the monthly consumer price index published by the Uganda Bureau of Statistics. Missing values are replaced with the sample average and a dummy for missing value for each variable is included in all regressions. ***denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Table A2: External Validity - Comparison with GEM Uganda Sample

Mean, standard deviation in parentheses

P-value on t-test of equality of means between baseline and GEM samples in brackets

	Number of firms	Owner gender [Female=1]	Owner age	Owner education	Owner started the business [Yes=1]	Number of owners	Firm Age [Years]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseline	2306	.532	34.5	2.48	.949	1.20	6.58
		(.499)	(7.49)	(.765)	(.220)	(2.43)	(4.76)
2010 GEM Uganda	762	.545	34.5	2.47	.934	1.43	6.36
		(.498)	(11.0)	(.801)	(.248)	(2.17)	(7.69)
p-value		[.799]	[.326]	[.326]	[.321]	[.060]	[.834]

Notes: The table reports summary statistics on basic owner and firm characteristics from baseline data and a comparison between firms at baseline and firms in the 2010 Adult Population Survey for Uganda conducted by the Global Entrepreneurship Monitor (GEM) project. In the baseline sample, the Owner education variable measures years of education. Education levels are instead coded in the GEM data using 1997 UN ISCED codes. These are: 2=Up to lower secondary education, 3=Upper secondary education, 4=Post-secondary non-tertiary education, 5=First stage of tertiary education, 6=Second stage of tertiary education. For the comparison with the GEM sample, the Owner education variable is recoded in the sample of firms from baseline to match 1997 UN ISCED education codes. Education levels in baseline data are translated into 1997 UN ISCED groups using the conversion table provided here: http://www.uis.unesco.org/Education/ISCEDMappings/Pages/default.aspx. The first two rows in columns (2) to (7) report means and standard deviations of each of the variables in the column headings for the baseline sample. Due to missing values, the actual sample sizes for the descriptives in the first and second row are the following (numbers in parentheses refers to column number): (2) 1,794, (3) 1,738, (4) 1,772, (5) 1,773, (6) 1,789, (7) 1,753. The fourth and fifth rows in columns (2) to (7) report means and standard deviations for the corresponding variables (when available) among the entire sample of firms included in the GEM sample (the sample here inlcudes all sectors, apart from agriculture/animal rearing). The sample is restricted to firms employing between 0-25 employees. Due to missing values, the actual sample sizes for the descriptives in the fourth and fifth row are the following (number in parentheses refers to column number): (2) 762, (3) 758, (4) 762, (5) 761, (6) 755, (7) 736. The p-values in brackets are from the t-test of equality of means between firms in GEM sample and firms in the baseline sample. ***denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Table A3: Measuring Labor Utilization

Sample Column 1: control firms at follow-ups 2-3-4
Sample Columns 2 and 3: workers at control firms at follow-ups 2-3-4
Sample Column 4 and 5: workers with labor utilization measured at control firms at follow-ups 2-3-4
OLS regression coefficients, robust standard errors in parentheses

	Labor Utilization Measure Can be Constructed			Labor Utilization	
	(1) Firms	(2) Workers	(3) Workers and Firm Fixed Effects	(4) Workers	(5) Workers
Monthly profits (log)	016				
	(021)				
Number of employees	0.016**				
	(008)				
Number of unskilled employees	-.086***				
	(015)				
Capital stock (log)	010				
	(015)				
Firm's age	004				
	(004)				
Age		001	- 002	002	005
		(002)	(003)	(003)	(004)
Sex (female)		- 034	- 011	018	032
		(035)	(046)	(044)	(077)
Tenure (months)		001	.001**	-.001	-.002**
		(000)	(001)	(000)	(001)
Primary school		.102*	093	030	044
		(052)	(065)	(048)	(075)
Junior Secondary school		072	069	033	032
		(051)	(065)	(046)	(076)
High Secondary school		056	050	010	010
		(061)	(074)	(059)	(084)
Certificate or higher		- 006	021	041	096
		(059)	(079)	(054)	(098)
Skilled		.328***	.337***	034	021
		(033)	(037)	(037)	(051)
Owner's family member		020	034	- 003	- 014
		(030)	(035)	(031)	(037)
Productivity (1-10)		.031***	.021***	- 007	- 002
		(006)	(006)	(006)	(008)
Received training		- 006	- 022	012	039
		(027)	(033)	(025)	(036)
Mean outcome	59 9	475	475	310	310
Survey wave fixed effects	Yes	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	No	Yes	No
Sector fixed effects	Yes	Yes	No	Yes	No
Other Firm Characteristics	Yes	-	-	-	-
Firm Fixed Effects	-	No	Yes	No	Yes
Number of firms	368	361	361	257	257
Number of observations	867	1790	1790	850	850

Notes: The unit of observation is the control firms (cols 1 and 6) and workers in control firms (cols 2-3-4-5) at follow-ups 2-3-4. All regressions include survey wave FE. Columns 1, 2, 4 include location (branch) and sector FEs. Columns 3 and 5 inlcude firms FE. In column 1 missing values for age, capital, firm's licence, profits, and num. of network firms are replaced with 0 and a dummy for missing values is included for each of the variables. The dependent variable in columns 1-2-3 is a dummy that equals 1 if the firm/worker have nonmissing value for labor utilization. The dependent variable in columns 4-5 is labor utilization. Labor utilization is computed as the percentage of hours workers typically spend at the firm during which they actually worked. Hours actually worked is calculated as follows. For each workers paid piece-rate, we ask the following three questions regarding a specific product/service: (1) How much time (minutes) would <name> normally take right now to complete his/her work on this product/service alone to a standard of quality considered satisfactory by the average customer of this business? (2) How much of the price charged to customers for this product/service does <name> normally receive? In addition, we have data on the total earnings of the worker in the month prior to the survey. We calculate the number of products/services the worker has worked on in the last month by dividing total earnings by the piece-rate. We then calculate monthly hours actually worked as the number of products/services the workers has worked on in the last month times the average time taken to complete the product/services, which therefore only reflects the hours spent on production. Manufacturing is a dummy that equal 1 if the firm's sector is tailoring, construction, or welding.

Table A4: Owner's time use

All firms at baseline

A. Time use

	% Owners	Hours/30 days	Hours/30 days | Spending any time on it
Training	509	256	502
		(5510)	(6870)
Assisting workers	830	630	759
		(8720)	(9050)
Looking for workers	168	213	127
		(1350)	(3100)
Looking for machines	396	430	109
		(1050)	(1440)
Looking for loans	115	85	807
		(428)	(1080)
Interacting with gov.	427	132	308
		(285)	(368)

B. Days spent at the premises & hours worked

	% Owners	Hours/normal day
Every day	850	108
		(256)
Several times a week	108	890
		(280)
Several times a month	239	825
		(318)
Once a month or less	179	559
		(439)
Average		104
		(284)

Notes: In Panel A, the hours/30 days variable is calculated as days spent doing a given activity in the last 30 days*hours/day spent doing that activity on a normal day. The variable hours/day is winsored at the top1% (among non-0 values). The list of activities were pre-specified.

Table A5: Percentage of Firms Adjusting Inputs

	Employees			Machines		
Survey Wave (follow-up)	**Any**	**Positive**	**Negative**	**Any**	**Positive**	**Negative**
1	71 6	39 7	62 3	23 3	18 8	8 3
2	55 9	32 4	39 9	21 9	18 8	4 3
3	58 6	40 4	43 0	30 3	28 2	9 4
4	58 7	40 1	42 7	35 2	30 4	10 0
All	91 5	75 2	86 4	63 9	59 0	24 2

Notes: Data from a monthly panel of firms in treatment group control. Panel A indicates the percentage of firms that adjusted their K/L residual ratio, labor, and capital at least once within each follow-up or within the entire study period. Panel B indicates the average and the median frequency of changes in K/L residual, labor, and capital (in months) including and excluding firms that never made adjustment in the variable of itnerest during the study period. If included, the number of months between changes equals the number of months in the study for the firms with no adjustments. For both panels, changes in number and capital are considered only for changes in numbers of employees or asset.

Table A6: Uncertainty, Utilization, and Employment, Robustness

Sample: Worker panel first follow-up (cols 1, 4, and 5) and firm panel first follow-up (col 8) and all follow-ups (other cols)
OLS and IV regression coefficients, robust standard errors in parentheses

	Hours spent in Production (workers)			Hours at the premises in the last month (workers)				Hours at the premises in the last month (owner)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PANEL A: Uncertainty										
Coefficient of Variation, *Expected* Monthly Revenues	-100.5***			-15.03	-31.08			-48.23		
	(28.42)			(17.75)	(31.28)			(30.01)		
Coefficient of Variation, *Current* Monthly Revenues		-16.53	-143.7***			.569	-12.39		3.832	1.663
		(14.52)	(46.96)			(6.903)	(28.26)		(8.573)	(36.52)
First Stage Coefficients:			.554***				.442***			.433***
Mean CV of monthly revenues, other firms			(.068)				(.048)			(.053)
Mean Outcome for Controls	35 2	75	75 6	281 65	265.503	272.471	272.296	336.765	326.636	326.914
Survey wave fixed effects	-	No	No	Yes	Yes	No	No	Yes	No	No
Sector and location fixed effects	Yes	No	No	Yes	Yes	No	No	Yes	No	No
Firm fixed effects	No	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes
Number of observations	528	1320	1291	1593	496	2189	2117	510	1990	1926

Notes: The table shows the results from a regression of a set of workers and firms characteristics on the coefficient of variation of expected and current monthly revenues. The unit of observation is the employee in Columns 1 and 4, and the firm in the remaining columns. The *coefficient of variation of expected monthly revenues* is only measured at first follow-up, and so the sample in Columns 1, 4, 5, and 8 only includes firms at first follow-up. In Columns 3, 7, and 10, for each firm, the coefficient of variation of firms' monthly revenues is instrumented by the average coefficient of variation of monthly revenues among firms in the same sector, branch, and survey round excluding the firm itself. *Hours at the premises in the last month (owner)* are computed multipling the average number of hours by the number of days the worker report being at the firm in a typical day. The *coefficient of variation of the firm's expected revenues* is calculated as follows. Each firm owner was asked the following questions: (1) Imagine that over the next 6 months the revenues from this business are very high. What is the maximum amount of revenues the ownercould make in the best month over the next 6 months? (2) Imagine that over the next 6 months the revenues from this business are very low. What is the minimum amount of revenues the owner could make in the worst month over the next 6 months? (3) In how many months over the next 6 months, does the owner think that the monthly revenues from this business' activities will be higher than (max-min)/2? We use these three questions to recover the owner's distribution of expectations, assuming a triangular distribution (Attanasio and Kaufmann, 2014). ***denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Table A7: Correlates of Wages and Asset Values

Sample: all firms at baseline. Unit of observation: unskilled workers (col 1), skilled workers (col 2), and firms (col 3)

OLS regression coefficients, robust standard errors in parentheses

	Log Unskilled Monthly Wages	Log Skilled Monthly Wages	Log Value of Main Asset in the sector
	(1)	(2)	(3)
Female Owner	036	034	009
	(077)	(049)	(067)
Owner Age	- 002	- 001	- 001
	(.004)	(.003)	(.003)
Firm Age	.012**	000	.017***
	(.005)	(.002)	(.005)
Firm has a Trading License	055	-0 108	.121*
	(.098)	(.067)	(.072)
Number of Workers	007	.018**	.086***
	(.009)	(.008)	(.011)
Hours worked in the Last Month	.299**	-0 046	
	(.151)	-0 112	
Employee Productivity [1-5 scale]	.105***	.137***	
	(.026)	(.027)	
Empoyee Tenure (years)	.048***	.023*	
	(.013)	(.012)	
Adjusted R-Squared	.242	.154	.593
Partial R-Squared:			
Firm characteristics	.054	.020	.048
Sector fixed effects	.048	.052	.491
Location fixed effects	.115	.074	.058
Location and sector fixed effects	Yes	Yes	Yes
Number of observations	1091	2561	1766

Notes: All variables are measured at baseline. The unit of observation is the worker in **Columns 1 and 2**, and the firm in **Columns 3**. Firms that do not employ skilled workers, unskilled workers, or the most commonly used asset in the sector are excluded from Columns 1, 2, and 3 respectively. The table shows the results from a regression of skilled workers' monthly wages (Column 1), unskilled workers' monthly wages (Column 2), and the value of the machine most commonly used in the sector (Column 3) on firm characteristics, worker characteristics, sector and branch fixed effects. Trainees are excluded from the sample. The top 1% of profit, hourly wages and asset values are excluded. All monetary variables are deflated and expressed in terms of August 2012 prices, using the monthly consumer price index published by the Uganda Bureau of Statistics. ***denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Table A8: Adjustment Costs and Firm Constraints

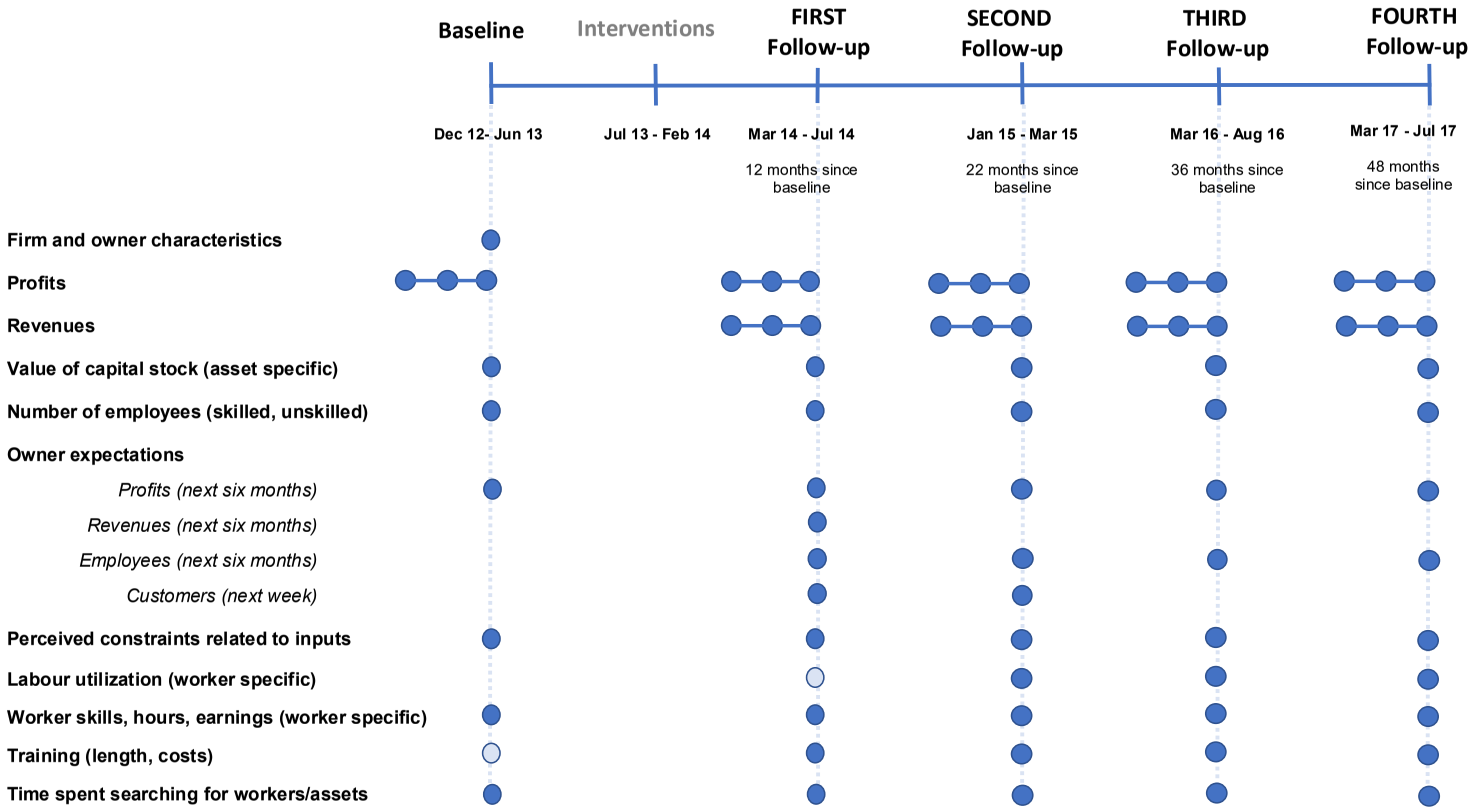
Sample: control firms follow-ups 1-2-3-4

OLS regression coefficients, robust standard errors in parentheses

	Residual K/L Ratio			
	(1)	**(2)**	**(3)**	**(4)**
Difficulty finding reliable machines	021		- 002	- 008
	(.143)		(.151)	(.155)
High cost of borrowing	- 125		- 128	- 149
	(.132)		(.135)	(.137)
Hours spent looking for machines in the last month	-.135***		-.086***	-.058***
	(0.016)		(0.017)	(0.017)
Hours spent looking for loans in the last month	-.033		- 018	- 012
	(.033)		(.033)	(.035)
Lack of skilled workers applying for jobs		- 013	- 022	- 047
		(.075)	(.075)	(.076)
Lack of trustworthy workers applying for jobs		- 012	056	105
		(.090)	(.095)	(.097)
Lack of unskilled workers applying for jobs		- 023	- 033	- 039
		(.069)	(.069)	(.071)
Difficulty screeing good workers		- 052	- 046	- 033
		(.083)	(.085)	(.087)
Inability to manage more employees		- 039	- 052	- 105
		(.066)	(.066)	(.064)
Hours spent training in the last month		-.149***	-.116***	-.152***
		(.016)	(.017)	(.017)
Mean outcome for controls	039	039	039	039
Survey wave fixed effects	Yes	Yes	Yes	No
Firm Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	3151	3151	3151	3151

Notes: The table shows the results from a regression of a measure of residual capital-labor ratio on several covariates. The unit of observation is the firm in a given survey round. All columns include firm FE. Columns 1 to 3 include survey round fixed effects. Residual K/L ratio is defined as the negative of the residual from a regression of the number of employees on the number of sector-specific machines of a given type utilized by the firm at baseline. Each machine type corresponds to a different explanatory variable. ***denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Figure A1: Study Timeline and Key Variables



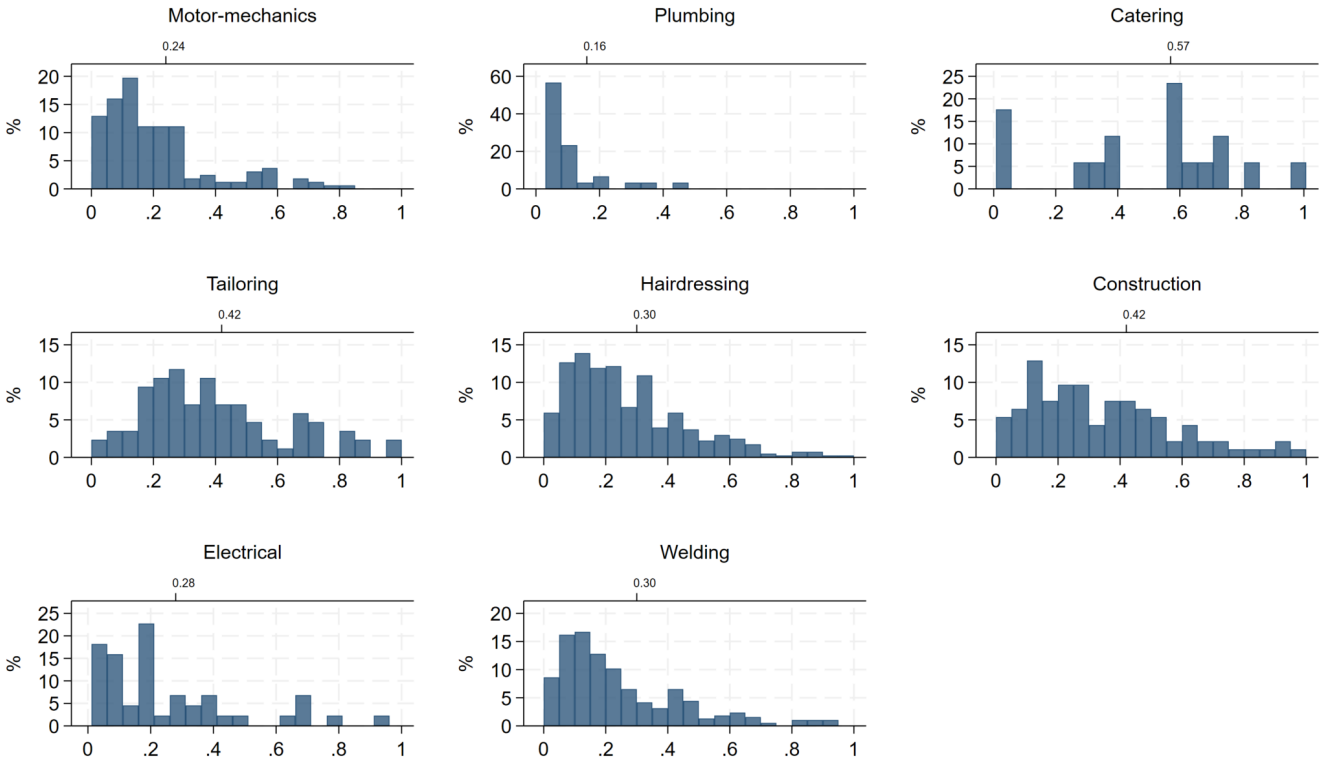
Notes: The firm level interventions include: Credit, List (Trained), List (Untrained), List+Wage Subsidy and Wage Subsidy. The Credit intervention was rolled-out throughout the intervention period. There were two round of the List(Trained) and List(Untrained) treatments, in line with the fact that there were two separate batches of trainees from the first round of applicants to the training program, one finishing in July and one finishing in October. The first round of the List (Trained) and List(Untrained) interventions took place in August-September 2013. The second round took place in December 2013-January 2014. The List+Wage Subsidy and the Wage Subsidy interventions took place in September-November 2013.

Figure A2: Sector-Specific Assets Questions

Trade specific equipment: Ask only about the equipment corresponding to the enterprise type				
Item	5.16 Does this business have access to **<item>**? ***See Response Options Below*** ***If 5.16=4 → next line***	5.17 How many **<items>** does the business have access to?	5.18 How much would it cost (UGsh) to purchase all **<items>** the business has access to in a similar condition today?	5.19 Is this item also used by the owner's household for non-business uses? 1=Yes 2=No
Hairdressing				
Hand hairdryer				
Scissors				
Tongs				
Hot comb				
(large) Dryer				
Sink				
Catering				
Pot				
Pan				
Stove				
Chafing dish				
Electrical Wiring				
Grinder				
Drilling machine				
Multi meter				
Tailoring				
Sewing machine				
Scissors				
Knitting machine				
Tape measure				
Responses for 5.16 1=Yes, own item 2=Yes, pay for the service but do not own 3=Yes, do not own item, but business has access without paying 4=No, do not own and do not have access				

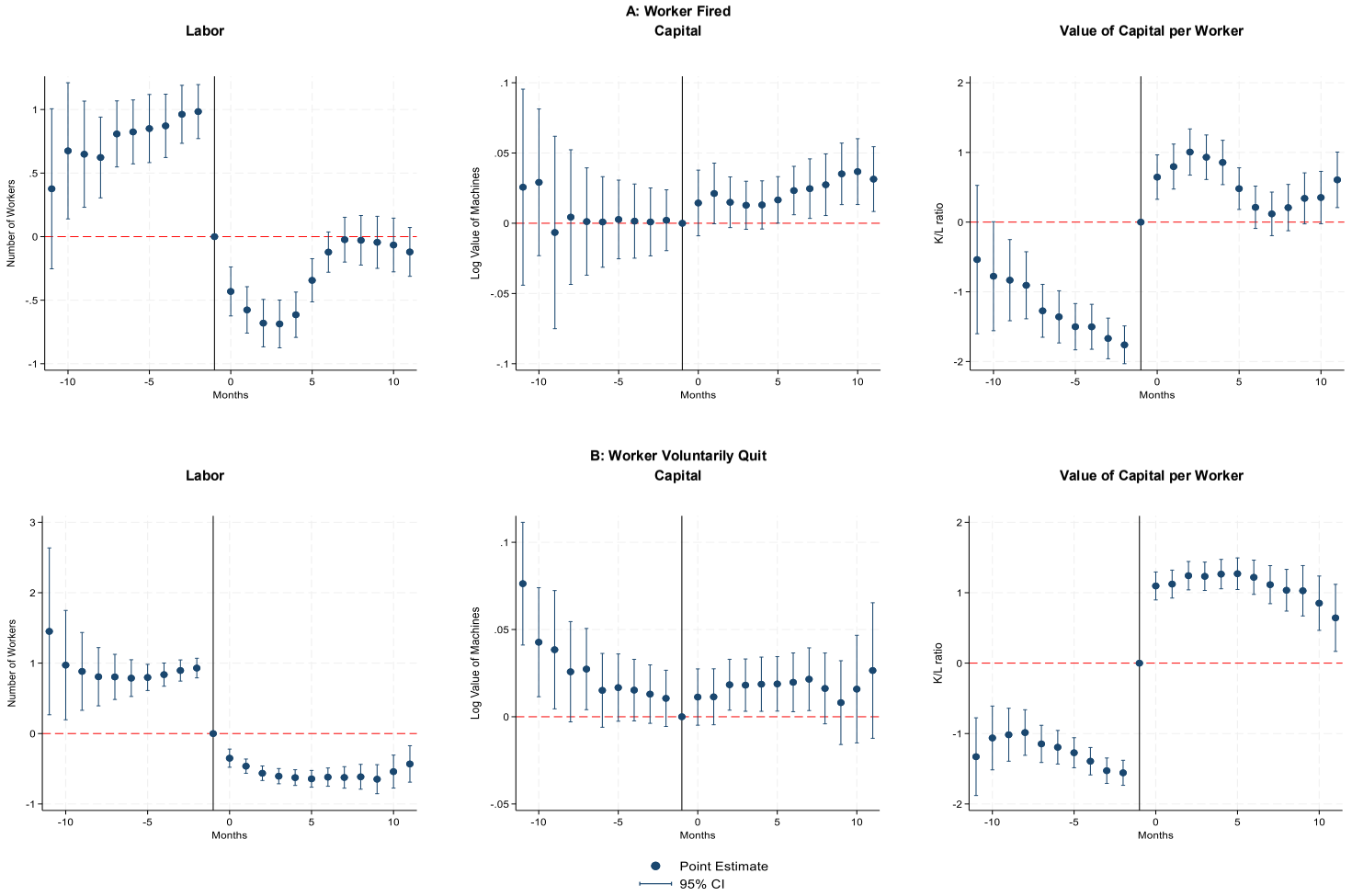
Figure A3: Labor Utilization, by Sector

Sample: Worker panel control firms follow-ups 2-3-4



Note: The figure uses worker-level data from the Control group at second, third and fourth follow-ups to show the distribution of labor utilization. Labor utilization is computed as the percentage of hours workers typically spend at the firm during which they actually worked. Hours actually worked is calculated as follows. For each workers paid piece-rate, we ask the following three questions regarding a specific product/service: (1) How much time (minutes) would <name> normally take right now to complete his/her work on this product/service alone to a standard of quality considered satisfactory by the average customer of this business? (2) How much of the price charged to customers for this product/service does <name> normally receive? In addition, we have data on the total earnings of the worker in the month prior to the survey. We calculate the number of products/services the worker has worked on in the last month by dividing total earnings by the piece-rate. We then calculate monthly hours actually worked as the number of products/services the workers has worked on in the last month times the average time taken to complete the product/services, which therefore only reflects the hours spent on production.

Figure A4: Reasons for Worker Separation Event Studies



Notes: These figures show event studies for the hiring of a new worker (Panel A), the firing or loss of a worker (Panel B), the purchase of a new machine (Panel C), the loss of a worker for reasons that did not depend on the owner (e.g., the worker left or died) (Panel D). The event is the hiring of a new worker (Panel A), and the firing or loss of a worker (Panel B), the purchase of a new machine (Panel C), and the non-volutnary loss of a worker (Panel D) in the 12 month before a given follow-up survey. The graphs show the results of the analysis pooled across all follow-ups. The outcomes are the logarithm of the firm's total value of assets over the number of workers employed at the firm, including the firm owner (K/L ratio), the number of workers employed at the firm, including the firm owner (Labor) and the logarithm of the firm's total value of assets (Capital).

Figure A5: Contract between BRAC and Firm Owners

Append Firm Owner's Photo Here

brac

Branch:

CONTRACT

Small Firm Expansion and Job Creation Program: Wage Subsidy (TA6)

I _____**(Firm Owner)** owner of_____**(Business Name)**

In _____**(Village/Area)** in _____**(Sub-County)**

Of _____**(County)** and _____**(District)**

hereby promise that I will conduct training for the undersigned trainee regularly as per the following terms:

1. I am bound to provide a training course on _____ (trade type) for the duration of six month, starting ___/ ___ / 2013
2. I will refund the full allocation given by BRAC for training cost should I fail to provide the training.
3. BRAC Uganda will provide 120,000 UGSH monthly to supplement training costs. I expect no other payments from BRAC, Uganda.
4. I will attend monthly meetings and training sessions as per the schedule provided the Job Placement Officer (JPO) or ELA Staff.
5. I will abide by the decisions of BRAC Uganda regarding changes to the schedule, content of training, or assignment of trainee. I will retain the trainee I select for 6 months.
6. I agree provide honest information to BRAC Uganda. I understand that falsifying documents, deceiving BRAC staff or bearing false witness will result in the immediate termination of the contract.
7. I commit to try my best to ensure to good quality skill development for the trainee through this training.
8. I confirm that I am physically able to conduct and compete the training.

I here by sign the promissory note with full conciseness after reading, fully understanding and accepting the conditions, without any influence from any one.

_____
Firm Owner's Full Name

_____
Trainee's Full Name

_____
Firm Owner's Signature

_____
Trainee's Signature

_____
Date

_____
Date

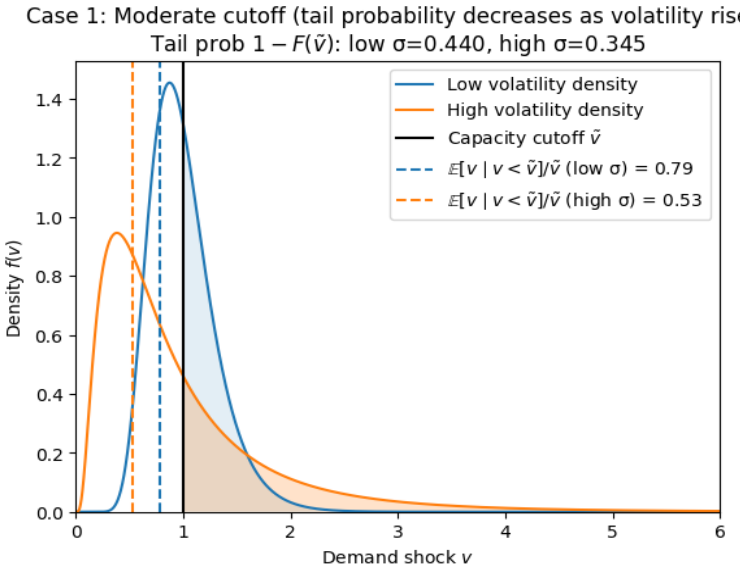
_____
JPO / ELA Staff Signature

_____
Date

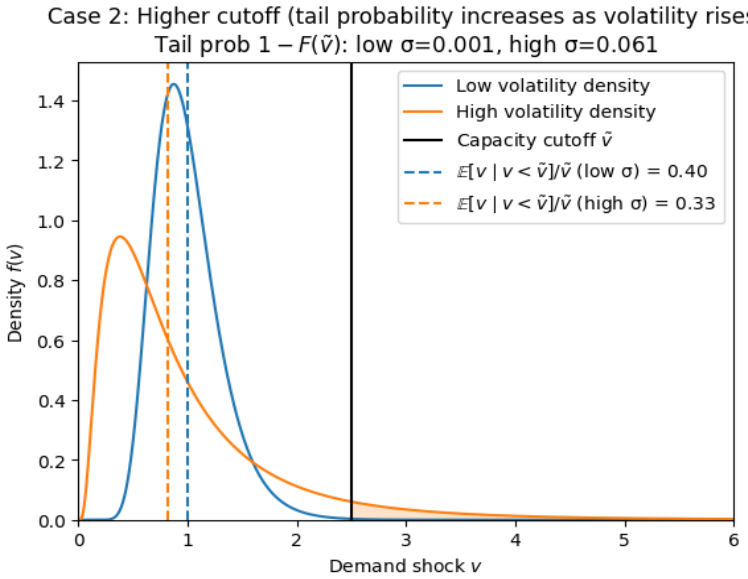
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Figure A6: Illustration of Proposition 1

Panel A: Moderate Cutoff



Panel B: High Cutoff



Appendix 2: Proofs

Appenidx 2.1: Proof of Proposition 1

Let $v \sim \text{Lognormal}(\mu_v, \sigma_v^2)$ with fixed mean $E[v] = e^{\mu_v + \sigma_v^2/2}$. Then $M_1(\tilde{v})$ and $\bar{F}(\tilde{v})$ are given by the following expressions:

$$M_1(\tilde{v}) = E[v]\ \Phi\Big(\tfrac{\ln(\tilde{v}/E[v])}{\sigma_v} - \tfrac{\sigma_v}{2}\Big), \qquad \bar{F}(\tilde{v}) = 1 - \Phi\Big(\tfrac{\ln(\tilde{v}/E[v])}{\sigma_v} + \tfrac{\sigma_v}{2}\Big).$$

At fixed $\tilde{v}$,

$$\frac{\partial E[u]}{\partial \sigma_v} = \frac{E[v]}{\tilde{v}}\,\phi(z_-)\left(-\frac{\ln(\tilde{v}/E[v])}{\sigma_v^2} - \frac{1}{2}\right) \;+\; \phi(z_+)\left(\frac{\ln(\tilde{v}/E[v])}{\sigma_v^2} - \frac{1}{2}\right),$$

with $z_\pm = \frac{\ln(\tilde{v}/E[v])}{\sigma_v} \pm \frac{\sigma_v}{2}$. Assumption (i) makes both brackets ≤ 0, hence $\partial E[u]/\partial \sigma_v < 0$. Moreover $\partial E[u]/\partial \tilde{v} < 0$ (since $u = \min\{v/\tilde{v}, 1\}$ is nonincreasing in $\tilde{v}$), and with inputs fixed we have $d\ln\tilde{v}/d\sigma_v = \theta\,\varepsilon_\mu \ge 0$ by (ii). Therefore

$$\frac{dE[u]}{d\sigma_v} = \underbrace{\frac{\partial E[u]}{\partial \sigma_v}}_{<0} + \underbrace{\frac{\partial E[u]}{\partial \tilde{v}}}_{<0} \cdot \underbrace{\frac{d\tilde{v}}{d\sigma_v}}_{\ge 0} \;<\; 0.$$

Appendix 2.2: Proof of Proposition 2

The first order conditions (11), (12), and (13) can be rewritten as:

$$(b): \quad (\mu(\tilde{v}) - 1)\, w \left[\frac{\alpha(1-\theta)}{\tilde{v}}\, M_1(\tilde{v}) + \bar{F}(\tilde{v})\right] \;=\; \chi(\tau)$$

$$(\tau): \quad (\mu(\tilde{v}) - 1)\, w\, \frac{(1-\alpha)(\theta-1)}{\tilde{v}}\, M_1(\tilde{v})\, \frac{\phi'(\tau)}{\phi(\tau)} \;=\; \chi'(\tau)$$

$$(k): \quad (\mu(\tilde{v}) - 1)\, w\, \frac{b}{k}\, \frac{\alpha(\theta-1)}{\tilde{v}}\, M_1(\tilde{v}) \;=\; r$$

(i) Training τ. Define $\Xi = (\mu - 1)M_1/\tilde{v}$. In the τ–FOC, the LHS is $\Xi \cdot C_\tau(\tau)$ with $C_\tau(\tau) \equiv w(1-\alpha)(\theta-1)\,\frac{\phi'(\tau)}{\phi(\tau)}$, which is *decreasing* in τ by concavity of ϕ. Under (ii), Ξ falls with σ_v, so to keep equality with $\chi'(\tau)$ (increasing in τ), τ must fall.

(ii) Capital k. In the k–FOC, $\Xi \cdot (b/k)$ is constant. Taking logs and differentiating,

$$\frac{d\ln k}{d\sigma_v} = \frac{d\ln b}{d\sigma_v} \;+\; \frac{d\ln \Xi}{d\sigma_v}.$$

Thus $dk/d\sigma_v < 0$ whenever $d\ln b/d\sigma_v < -d\ln\Xi/d\sigma_v$ (> 0). If in particular b is weakly nonin-

creasing in σ_v, then k strictly decreases.

(iii) Blueprint Labor b. Let

$$G(b,k,\tau;\sigma_v) \;\equiv\; (\mu(\tilde{v})-1)\,w\left[\underbrace{\frac{\alpha(1-\theta)}{\tilde{v}}\,M_1(\tilde{v},\sigma_v)}_{\text{slack/price (MC) channel}}+\;\underbrace{\bar{F}(\tilde{v},\sigma_v)}_{\text{capacity channel}}\right]-\chi(\tau)=0,$$

be the b-FOC, with $\tilde{v}=q\,p^{\theta}$ and $q=Ak^{\alpha}(b\phi(\tau))^{1-\alpha}$. By the implicit function theorem,

$$\frac{db}{d\sigma_v} \;=\; -\,\frac{G_\sigma}{G_b}.$$

Volatility derivative G_σ. Write $B(\tilde{v},\sigma_v)\equiv\frac{\alpha(1-\theta)}{\tilde{v}}M_1(\tilde{v},\sigma_v)+\bar{F}(\tilde{v},\sigma_v)$. Then

$$G_\sigma=(\mu(\tilde{v})-1)w\Big[\,B_\sigma+\,B\Big]+w\Big[\,B_{\tilde{v}}+\,B\Big]\frac{d\tilde{v}}{d\sigma_v}.$$

At a fixed cutoff $\tilde{v}$,

$$B_\sigma=\frac{\alpha(1-\theta)}{\tilde{v}}\quad\underbrace{\frac{\partial M_1}{\partial\sigma_v}}_{<0\text{ if }\tilde{v}\geq E[v]}\quad+\quad\underbrace{\frac{\partial\bar{F}}{\partial\sigma_v}}_{\text{sign not pinned by }\tilde{v}\geq E[v]}\quad.$$

Since $\alpha(1-\theta)<0$, the first term in B_σ is *positive*; the second term has *no definite sign* unless one imposes extra restrictions on the location of $\tilde{v}$ (e.g. $\tilde{v}\lessgtr E[v]e^{\sigma_v^2/2}$ in the lognormal case).

The via–cutoff part multiplies

$$B_{\tilde{v}}=\alpha(1-\theta)\Big[f(\tilde{v})-\frac{M_1(\tilde{v})}{\tilde{v}^2}\Big]-f(\tilde{v}),$$

whose sign is *parameter-dependent* (it loads on $\alpha(1-\theta)$ and compares $f(\tilde{v})$ to $M_1(\tilde{v})/\tilde{v}^2$). The multiplier $d\tilde{v}/d\sigma_v$ is itself ambiguous and depends on θ and α through pricing/markup and the re-optimized responses of k,τ,b. Therefore, G_σ it has no determinate sign in general.

b-derivative G_b. Since b enters the FOC through $\tilde{v}$,

$$G_b=(\mu(\tilde{v})-1)w\Big[\,B_{\tilde{v}}+\,B\Big]\cdot\frac{\partial\tilde{v}}{\partial b},\qquad\frac{\partial\ln\tilde{v}}{\partial\ln b}=1-\alpha+\alpha\theta>0.$$

While $\partial\tilde{v}/\partial b>0$, the factor $\big[B_{\tilde{v}}+B\big]$ has *no definite sign* because $B_{\tilde{v}}$ is ambiguous (see above). Thus G_b is not sign-definite either.

Since both G_σ and G_b are sign-indeterminate under the mild assumption $\tilde{v}\geq E[v]$, the ratio $-G_\sigma/G_b$ (and hence $db/d\sigma_v$) is *ambiguous*. The parameters θ and α are pivotal: the slack/price term scales with $\alpha(1-\theta)$ (higher θ or higher α strengthens the negative price channel), while the capacity effect depends on how $\tilde{v}$ and the tail probability $\bar{F}(\tilde{v})$ move with σ_v, which in turn load on θ (via markups) and on α (via how b shifts capacity relative to marginal cost).

Appendix 3: Additional evidence of adjustment costs

To quantitatively examine adjustment costs, we need to construct a measure of the relative capital and labor adjustment costs for each firm. We do so by leveraging our detailed asset and worker rosters to construct a measure in two steps. First, we use the baseline data to estimate a LASSO regression of the number of workers employed by a firm on a vector containing the number of machines of each type used in production, controlling for sector fixed effects. We use this to select the sector-specific asset types that are most predictive of employment. Second, we estimate the following specification again using only the baseline data:

$$L_{jsl} = \alpha + \sum_{k=1}^{k} \beta_k K_{jk} + \delta H_j + \gamma_s + \gamma_l + \varepsilon_{jsl}, \tag{A.1}$$

where L_{jsl} is the number of workers employed in firm j, operating in sector s and location l. K_{ik} is the number of type-k assets used by firm j, with asset types restricted to those selected via LASSO. H_j is the share of high-skill workers employed in firm j. γ_s and γ_l are sector and location fixed effects, which control for differences in production functions across sectors, and differences in input prices across locations.

We define our relative measure of adjustment costs as the negative of the residual from (A.1), $-\widehat{\varepsilon}_{jsl}$, referring to this as the *residual capital-labor (K-L) ratio*. Firms with a higher residual K-L ratio have fewer workers than predicted by the number and types of assets they use in production, conditional on sector, input quality, and input prices. We attribute this residual heterogeneity to differences in relative adjustment costs, so a higher residual K-L ratio captures higher adjustment costs in labor relative to capital. Intuitively, firms with high capital adjustment costs will choose *lower* levels of capital relative to labor, as machines are the more costly input to adjust in response to demand volatility.[18]

One concern with the residual K-L ratio measure is that it is measured at baseline, but could by volatile over time. If so, it is difficult to interpret it as a measure of underlying firm heterogeneity. We validate the measure in Table A9 by correlating it with reported constraints over time. To do so we fix the LASSO selected machines and coefficients estimates from baseline, but then update the measure of the residual K-L ratio based on the actual number of workers and machines the firm has access to on each follow up survey. We see that when we consider both capital and labor

[18]Two further points are of note. First, our preferred measure of adjustment costs is highly correlated with alternative constructed measures that exclude rented machines ($\rho = 1.00$), include non sector-specific assets ($\rho = .978$), use log of machine values ($\rho = .930$), or include interactions between different types of machines within sectors ($\rho = .973$). Second, following Bassi *et al.* [2022], this approach implicitly assumes constant wages and capital rental prices within sector-branches (*sb*). Table A8 explores further the determinants of inputs prices at baseline. They partial R-squared at the foot of each Column shows that firm characteristics explain very little of the observed variation in input prices. Location fixed effects explain a larger share of the variation in wages (Columns 1 and 2) than firm fixed effects, while sector fixed effects explain nearly half the variation in the value of key machines (Column 3).

related constraints, firm have significantly lower residual K-L ratios if owners spend more time searching for machines or training workers.

Columns 4 and 5 of Table 5 examines the relationship between labor utilization and our measure of adjustment costs. Controlling for sector, location and survey wave fixed effects, we find a positive relationship between labor utilization and the residual K-L ratio, in line with firms with higher labor relative to capital adjustment costs utilizing workers more intensively. In Column 5 we use the worker and asset rosters to construct the residual K-L ratio at each follow-up and repeat the same regression with firm fixed effects. We continue to find a positive relationship between labor utilization and the residual K-L ratio. Intuitively, firms with higher labor adjustment costs have relatively fewer workers, as finding and training workers is more costly for them, and therefore they tend to use their existing workers more intensively.