MEASURING THE IMPACT OF IMPACT MEASUREMENT

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Abstract. Impact measurement is central to impact investing and social entrepreneurship. What is the consequence of impact measurement on firm performance and the allocation of capital? We study an impact measurement course for high-growth social enterprises, randomizing which firms receive hands-on support. Treated firms exhibited nearly twice as much revenue growth and capital raised. In a companion experiment, we find that professional investors have a strong preference for firms that can demonstrate quantifiable impact over those that make non-quantified impact statements.

We thank Beyonce.

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I. Introduction

The last two decades have seen tremendous growth in the legitimacy of the movement to combine social impact with corporate interests. Leading estimates suggest that impact investors control more than one and a half trillion dollars in assets under management (Hand et al., 2024), and that social enterprises generate more than two trillion dollars in annual revenue worldwide (World Economic Forum and Schwab Foundation for Social Entrepreneurship, 2024). It is widely agreed upon that to achieve the movement's social objectives, the measurement of impact must be elevated to the same level of rigor as that of profits (Serafeim and Trinh, 2020). Indeed, the Global Impact Investing Network's (GIIN) definition of impact investing requires that an investor explicitly measure their own impact. How should impact be measured across the industry? How do rigorous impact measurement practices affect the firms that adopt them?

We investigate these questions through two field experiments with social enterprises and investors. The first experiment was conducted in partnership with Villgro – India's largest incubator of social enterprises. Our experimental sample comprises 146 social enterprises spanning industries such as agribusiness, health, energy, and education. Roughly a third of the sample was pre-revenue, a third had a product in market, and a third was actively seeking growth capital, with the average firm in our sample having annual revenue of USD 52,000 and having raised USD 93,000 in financing at baseline.

All participating social enterprises were enrolled in a thirteen week impact-measurement course, intended to represent the gold-standard in the industry. The course covered three frameworks for measuring impact. The first two of these – the IRIS+ framework developed by the GIIN, and Acumen's lean data approach – are among the most popular impact measurement approaches in the industry. The third – the measurement of consumer, employee, and supplier surplus – is less common, but is grounded in foundational economic theory and is easily interpretable across firms in diverse sectors. Alongside these approaches, participants also engaged with leading frameworks for communicating their impact to various stakeholders, including customers, employees, and investors.

While all participating firms took the course, those randomly assigned to be in the treatment condition of our experiment received additional hands-on support to operationalize these frameworks. This support took two primary forms. First, firms in our treatment condition had access to a representative from Villgro for one-on-one meetings. As each of the impact measurement frameworks require surveying a firm's customers, the representative helped firms both to select the framework that best suited their needs, and to devise and deploy customer surveys to populate the framework. Firms typically met with their representative four to five times. The second form of support is that the research team conducted an impact measurement survey of treatment firm's customers, employees, and suppliers, collecting data on consumer, employee, and supplier surplus, and delivered a report to each firm communicating their impact. These reports were intended to

be shared with investors and employees. The control group received no additional support beyond attending class sessions, though at the end of the experiment, the research team collected consumer, employee, and supplier surplus data on their behalf as well.

The intervention had a large impact on both revenue growth and access to capital. While over the course of our experiment, control group firms saw a growth in annual revenue of about USD 24,000, those in the treatment group experienced about USD 20,000 in additional revenue growth – nearly double. Similarly, while control group firms raised about USD 38,000 in outside capital in the year following the course, treatment group firms raised an additional USD 43,000 – again a doubling. While we do not pin down the precise mechanisms that drive these results, we argue that two are the most likely. First, each of the impact measurement methods requires engaging directly with customers to understand which ones derive the most value from the firm's products and services, and which products and services are the most valued. These initiatives are likely to accelerate the firm's search for product-market fit (Gans et al., 2019). Second, the course equipped firms with the tools to credibly communicate their impact to investors, increasing the likelihood of successfully raising capital. And these two channels likely feed into one another, as revenue growth increases the likelihood of raising capital, and raising capital increases the firm's potential to grow revenue.

Our second experiment directly measures how investors respond to rigorous impact metrics. We conducted a framed field experiment with 223 early-stage investors with experience investing in Indian startups. These were recruited through Villgro and Harvard Business School networks, through direct Linked-in outreach, and through the professional survey firm Dynata. Investors were shown hypothetical startup profiles, with characteristics drawn at random from the distribution of startups participating in our first experiment. Investors then rated these profiles based on their investment interest. Ratings were incentivized by the offer to introduce investors to real startups seeking capital, whose characteristics matched the preferences investors expressed through their ratings. Randomizing firm attributes allows us to infer the causal impact of any firm characteristic on investor interest, holding other firm characteristics constant.

Our primary comparison of interest is in the way a startup's social impact is communicated. Some profiles contained no explicit information about social impact. Some contained an "impact statement," meant to represent the non-quantitative approach to communicating social impact adopted by many social enterprises. And some profiles contained a measure of the consumer surplus generated by the firm—one of the key quantifiable impact metrics covered in the social enterprise training from our first experiment.

Our main result is that investor interest is quite responsive to quantitative social impact metrics. Moving a startup from below- to above-median social impact, as measured by consumer surplus, is associated with an increase in investor interest that is comparable in magnitude to that of moving the firm from unprofitable to profitable. In contrast, investors are not responsive to non-quantitative

metrics of social impact; the impact statements had small and statistically insignificant impact on investor interest. The results of this experiment complement the first in establishing investor responsiveness to quantitative, easily interpretable metrics of social impact.

Our results contribute to several literatures. First is the literature establishing the importance of impact measurement for impact investing and social entrepreneurship (e.g. Serafeim et al., 2019; Allcott et al., 2023). Most related is the work establishing a link between social impact and firm performance (e.g. Kramer and Porter, 2011; Edmans, 2011; Eccles et al., 2014; Henderson and Steen, 2015; Khan et al., 2016; Lins et al., 2017). We advance this literature by establishing a causal link between impact measurement and firm performance through a randomized experiment.

We also contribute to the literature experimentally evaluating the impact of various training programs on startup growth. Camuffo et al. (2020) and Lee et al. (2024) both find that entrepreneurship training programs cause startups to more quickly abandon their ideas, and improve firm outcomes conditional on persevering. Camuffo et al. (2024) presents a larger replication of Camuffo et al. (2020), which confirms the effects on firm exit, but finds more nuanced conclusions on firm performance. We contribute to this literature by studying the impact of a training program explicitly targeted towards social enterprises, and focusing on impact measurement, demonstrating that this type of program can have meaningful consequence on firm growth and ability to raise capital. Our work also complements the large literature on firm training programs beyond high-growth startups, both with larger firms (e.g. Bloom et al., 2013) and microenterprises (e.g. Karlan and Valdivia, 2011).

Finally, our work relates to the literature evaluating the social preferences of investors, particularly through survey experiments. Much of this literature has explored how social impact factors into investors' objective functions. For instance, Humphrey et al. (2021) identifies asymmetries between social benefits and harms, Heeb et al. (2023) argues that investors respond to relative, but not absolute, levels of impact, and Bonnefon et al. (2025) and Green and Roth (2025) characterize the degree to which investors have consequentialist social preferences. We contribute to this literature by demonstrating that investors care about the manner in which social impact is communicated—they have a strong preference for quantifiable information about social impact, relative to non-quantified social impact statements.

II. Experiment Overview

Our experiment was conducted with Villgro, India's largest incubator of social enterprises. Representatives from Villgro, and professors from Harvard Business School and the University of Chicago Booth School of Business conducted a course on impact measurement and management that all startup participants—in both the treatment and control conditions—were invited to attend. The treatment group received several additional means of support to operationalize the frameworks and techniques from the course and bring them into practice. In what follows we describe the course and intervention, then describe our data and sample summary statistics, and finally present the results.

A. Impact Measurement and Management Course

Startup participants were recruited through Villgro's network. Active startups that had participated in previous Villgro programs, attended Villgro events, or otherwise had indicated a desire to be notified of Villgo programming were directly contacted to participate in the course. Representatives from Villgro also circulated several announcements of the course through its social media accounts. All startups with a social impact focus were invited to apply to the program.

In total, 167 startups participated in the course.[1] The two primary selection criteria were that the startup conveyed plausible ambitions to achieve significant scale and social or environmental impact, and that a founder or member of the executive team had committed to attend the majority of the course sessions, should they be invited to enroll. We defer the description of the participating firms to the following section.

The course ran from April to June of 2023, in seven two-hour sessions taking place over Zoom, every other week.[2] The course covered three main components. First, participants learned to outline their theory of change—the mapping from their core business activities and outputs to societal or environmental impact—and to make explicit the assumptions required for their business activities to have their intended impact. Second, participants were introduced to three methods for collecting data to measure their social or environmental impact—these are detailed below. Finally, the course covered tactics on effective communication of social and environmental impact to employees, donors, and investors, and included a demo for making polished "impact reports" through software from the company Sopact. The three methods for measuring social impact are as follows.

GIIN IRIS+. The Global Impact Investing Network's (GIIN) Impact Reporting and Investment Standards (IRIS+) is one of the most widely used frameworks for measuring social impact in a

[1] In fact, 215 firms were selected to participate in the program, but by the time the program began, 48 had dropped out (prior to randomization).

[2] Representatives from Villgro engaged lightly with participating startups, both in treatment and control, starting from October 2022. This primarily entailed pre-readings distributed over email and Whatsapp.

corporate setting. For a startup in a given sector, it identifies a small handful of "key performance indicators" (KPIs) to track their social impact, and provides relevant empirical studies that map KPIs to social impact. For instance, a fintech lender may be guided to track the income and debt levels of their borrowers and track their borrowers' income-growth over time. They may also be pointed to several studies that have evaluated the impact of financial inclusion on livelihood growth and consumption smoothing, as a means to substantiate the link between the KPIs they monitor and the social impact they aspire to create.

Acumen's Lean Data Approach. In contrast to IRIS+, Acumen's Lean Data approach emphasizes generating short surveys and fielding them with a representative set of a business' customers to form a richer qualitative picture of its impact. For instance, the same fintech lender above might be guided to create a 15 minute survey for its borrowers, asking them to describe how they used their loan and the consequences of that expenditure on their household. The result may be a handful of selected anecdotes that are representative of how borrowers use their loans.

Consumer/Producer/Supplier Surplus. Participants were exposed to the idea of measuring the economic surplus provided to various stakeholders, as a summary statistic for social impact. In this approach, they were instructed to survey customers about their most recent transaction, eliciting both the amount paid and their self-reported willingness to pay for the product or service. Participants were taught that the difference between willingness to pay and amount paid is a measure of the value customers retain from the product or service, after accounting for their expenditure. They learned analogous methods for measuring employee and supplier surplus, where the latter was primarily relevant for firms that source inputs from smallholder farmers or other low-income suppliers.

Of course, none of these approaches is without weakness, and participants were invited to compare and contrast across them to identify their relative strengths. Overall, the impact training course covered two of the most common approaches to measuring impact in practice—GIIN's IRIS+ framework and Acumen's Lean Data approach, alongside the less-standard, though more economically interpretable approach of measuring consumer and producer surplus.

Finally, all firms enrolled in the course—in both treatment and control—were invited to participate in a matchmaking event between the firms and Indian venture investors. We describe the matchmaking exercise and the resulting preference data from the Indian venture investors in Section III.

B. Intervention

While all participating startups were invited to attend the course, startups assigned to the treatment group received several additional forms of support to put the lessons into practice. First, each treatment-group startup was assigned a representative from Villgro. Startups typically met with their assigned representative for four to five one-on-one sessions, in which the representative

helped them identify the impact measurement framework that most suited them, and would provide guidance on how to operationalize it. All three impact-measurement approaches require collecting bespoke survey data from customers, and sometimes employees and suppliers, and the Villgro representatives provided concrete guidance on how to conduct these data collection efforts.

Additionally, treatment group startups were divided into six sector-specific subgroups, broadly aligned around healthcare, waste management, education, agriculture and food, and climate and the environment. Each subgroup was placed into a WhatsApp group and invited to a Zoom session where they could share sector-specific insights related to impact measurement and management.

Finally, in October of 2023, the research team provided data collection services for treatment startups. Treatment group startups were invited to submit a list of phone numbers of select customers, employees, and suppliers who were then surveyed to elicit self-reported measures of consumer, employee, and supplier surplus. Each participating startup received an impact report, summarizing the data specific to their firm and explaining why measures of consumer, employee, and stakeholder surplus can be interpreted as a measure of social impact—see Online Appendix Figure B1 for an example report. In May of 2024, at the culmination of the study, both treatment and control startups were invited to participate in a final round of data collection to elicit customer, employee, and supplier surplus. All participating startups received an analogous impact report.

Figure 1 depicts the timing of our intervention and data collection.

C. Data and Descriptive Statistics

Our analysis draws primarily on two surveys of participating startups. Baseline data come from the applications that startups submitted to participate in the training program. These data were collected in September 2022 and contain information on firm characteristics (incorporation year, sector, target customers), and firm financials (revenues, profits, employees, equity, debt, grant capital raised to date).

Our endline survey data were collected in July of 2024 and have information on revenues and profits in the years 2023, 2022, and 2021. One limit of our data on firm profits is that 33% of firms reported a value of 0 to indicate that they are not yet profitable. As such, in the analysis to follow, we only analyze whether a firm has reached profitability, rather than analyzing our intervention's impact on profits in levels. Our endline data also contain information on the amount of debt, equity, and grant capital raised to date.

As described above, we also collected two rounds of data from firms' customers, employees, and suppliers—one round for the treatment group in October 2023 and one round for both treatment and control firms in May 2024. This data contains information on customers' most recent transaction, including the amount of money they paid and their stated willingness to pay, information on employees' salary and the smallest salary they would require to stay at their job, and information

on suppliers' most recent transaction including how much they were paid and the least they would have been willing to sell their goods for.

We view the consumer, employee, and supplier surplus data as potentially useful inputs for firms seeking to learn about their stakeholders and communicate impact. However, for the purposes of our analysis, measurement noise combined with substantial heterogeneity in stakeholder populations across firms makes cross-firm comparisons and treatment-effect estimates imprecise in our relatively small sample. For this reason, as well as the fact that data collection was staggered across treatment and control, introducing comparability issues, we have opted not to present analyses of these data.

In total, 167 firms participated in the program and submitted baseline data. We have removed 4 of these firms from the analysis, whose annual revenue exceeds USD 1 million. Table A1 presents the differences between these 4 firms and average values for the 163 firms we utilize in our analysis. While the 4 outlier firms are similar to the remainder on many firm characteristics, they have 32 times as much average annual revenue and more than 14 times as many employees.

For our main analysis, we top-code all outcome variables at the 95 percentile, but show the robustness of our results to topcoding at the 99th percentile.

Table 1 presents our sample descriptive statistics. About 26% of the firms in our sample are in the "minimum viable product" stage, indicating that they have not yet generated revenue, about 32% have launched a product in the market, but have not raised significant capital, and about 42% are in their "growth stage," indicating they have raised significant outside financing.[3] 26% of our sample is in agri-business, about 22% is in health services, about 22% is in energy and clean tech, 7% is in education, and about 14% focus on improving livelihoods and skill acquisition.[4] Average annual revenues at baseline were about USD 75,000, firms have on average 12.5 employees, and they have raised on average USD 130,000 in outside capital. Across all of these variables, the only statistically significant difference between treatment and control firms is that the treatment firms are 11.8 percentage points more likely to be in energy and clean tech (p-value = 0.06), and an F-test does not reject that the two samples are drawn from the same distribution (p-value = 0.83).

Finally, Table A2 examines attrition in our endline survey. We find no evidence of differential attrition. We failed to collect outcome data for 21 firms in each of treatment and control (25.3% of treatment firms and 26.2% of control firms). We find no statistically significant differences in the characteristics of attriting firms across treatment and control – the largest differences in magnitude are that attriting control firms had an additional USD 34,000 in baseline revenue, but raised USD

[3]These categories are self-assigned by each responding firm.

[4]Examples of companies in agribusiness include those that produce, source, and process organic products from farmers, those that provide consulting for farmers, connect farmers to markets, and deploy technical innovations to increase yields. Companies in the health sector include those that provide telehealth consultations, mental and physical health applications, and those that develop novel technologies like prosthetics and biometric monitors. Examples in the energy and clean tech sector include companies that facilitate recycling and the disposal of e-waste, companies that manage microgrids, and water management and purification. Examples of companies in the education sector include those that are providing e-learning solutions for psychosocial skills, coding, and general education. Finally, companies in the livelihood sector include those that manage HR platforms and marketplaces for vendors.

133,000 less in outside capital. An F-test does not reject that the two samples of attriters are drawn from the same distribution (p-value = 0.50).

D. Results

To estimate the impact of our intervention we employ a difference in difference design. Specifically, we estimate

$$y_{it} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Post_t * Treat_i + \varepsilon_{it} \tag{II.1}$$

where y_{it} is our outcome of interest for startup i in period t, $Treat_i$ is an indicator for whether startup i is in our treatment group, and $Post_t$ is an indicator for whether the outcome corresponds to a period after our intervention began. In alternative specifications we include firm fixed effects. Standard errors are clustered at the firm level, and to account for our relatively small sample, we report both p-values based on traditional standard errors as well as wild cluster bootstrap (Cameron et al., 2008).

For revenues and profits, we utilize three pre-intervention data points: our baseline survey elicited the average value over FY2021 and FY2022, and our endline survey retrospectively elicited the values separately for FY2021 and FY2022. We treat each of these three data points as a unique pre-intervention observation. The post-period observation is firms' profits and revenues in FY 2023, drawn from our endline survey. As we did not elicit retrospective data from our pre-intervention period in our endline survey on other outcome variables, for all other outcomes, our pre-period outcome data contain only one observation drawn from the baseline survey, and our post-period outcome data contain only one observation drawn from the endline survey.

Our results on firm revenue, profits and capital raised are presented in Table 2. Even columns contain firm fixed effects. As discussed above, our measure of profits is a binary indicator of whether the firm has reached profitability. The coefficient on $Post_t$ indicates significant growth in control firms over our study period; annual revenue grew by about USD 24,000, firms were 16-19 percentage points more likely to be profitable, and firms raised about USD 38,000 in additional outside capital. All of these estimates are statistically significant at the 1% level, except for firm profitability in column 4, which is statistically significant at the 5% level. The coefficient on $Post_t * Treat_i$ indicates that growth in revenue and capital raised was about twice as large for firms in the treatment group. For instance, column 2 indicates that treatment firms had an additional annual revenue growth of USD 20,210 (wild bootstrap p-value = .03), and column 6 indicates that treatment firms raised an additional USD 43,110 in outside capital (wild bootstrap p-value = 0.03). We do not find any impact on whether a firm reaches profitability, but this is unsurprising given that many startups prioritize expanding revenue over achieving profitability. The estimates are highly stable to the inclusion of firm fixed effects.

Figure 2 plots kernel densities for the increase in revenues and capital raised across our intervention period, separately for treatment and control firms. The figures demonstrate that the treatment effect on both revenue and capital raised is apparent across nearly the full distribution of firm outcomes. Online Appendix Table A3 replicates the analysis of Table 2, top-coding outcome variables at the 99 percent level rather than 95 percent level. Results are similar in direction and magnitude, though the estimates are somewhat noisier. With the exception of the impact on firm revenues, the coefficient on $Post_t * Treat_i$ is not statistically significant.

Finally, Online Appendix Table A4 reports treatment effects on the type of capital raised: equity, debt, and grants. Column 1 indicates that treatment firms raised an additional USD 18,580 in equity capital (wild bootstrap p-value = 0.02), and column 3 indicates that they raised an additional USD 10,110 in debt (wild bootstrap p-value = 0.03). While the point estimate on grant capital is also positive in columns 5 and 6, it is not statistically significant. Once again, estimates are highly stable to the inclusion of firm fixed effects.

E. Mechanisms

Several mechanisms may drive our interventions' impact on revenue and capital raised. First, each of the three methods for measuring impact covered in the course requires employees of a firm to interview their customers about the value that the firm creates. In doing so, firms may have gathered information about what types of customer they best serve, and how to better deliver value. These tactics are closely aligned with "best practices" taught in marketing courses in business schools, and are often thought to be valuable for early stage firms to develop more informed views about how to drive customer value. This could directly lead to revenue growth.

Second, the impact measurement course may have increased the credibility with which founders pitched impact investors to raise capital, both by giving them a more structured language for discussing impact, and by giving them the tools to put data behind their impact claims. In fact, part of the intervention was to collect customer, employee, and supplier surplus data and deliver it to treatment-group startups in a polished report that could be shared with investors—see Online Appendix Figure B1 for an example report. We provide further evidence for this channel in the following section.

These two channels also feed one another, as faster revenue growth is attractive to investors, and raising additional capital is an input into revenue growth.

A third potential channel for these results is that by encouraging firms to measure customer surplus, they may have become more informed about their demand curve and more effectively tailored their prices to maximize revenue. We do not have reliable data on firm prices, but quantifying the strength of this channel is an important avenue for future research, as price impacts would have ambiguous welfare implications.

A final mechanism, which we do not think is at play, is that treatment firms benefited from a "certification effect" from having taken the course, which helped them raise capital. We emphasize that all study participants, in both the treatment and control conditions, took the course and received the certification. The intervention was meant to increase the value of the course for treatment firms by helping them operationalize the lessons, while holding any resulting certifications constant across treatment and control firms.

III. Investor Survey

The experiment in the previous section indicates that encouraging startups to collect rigorous impact data helps them generate revenue and raise additional capital. How do investors interpret and use quantitative impact metrics in evalauting startups? To address this question, we conducted an incentivized survey experiment with professional venture investors, eliciting their preferences over startup profiles that vary in whether and how they report impact metrics. In line with our first experiment, we document a substantial preference for startups that report strong impact metrics. In contrast, *qualitative* impact statements, those that do not yield a quantitative interpretation, do not factor heavily in investor preferences. We begin this section with a broad overview of the survey experiment, and then proceed to outline recruitment, implementation, and results.

A. Survey Overview

Between April 2024 and August 2025, we implemented an incentivized, randomized survey experiment to study investors' preferences for India-based social enterprises, focusing on the causal effect of social impact information on investment propensity. Our design closely follows Colonnelli et al. (2024) and is inspired by the non-deceptive rating framework of Kessler et al. (2019). The core experimental task asks investors to evaluate a set of synthetic company profiles. Each profile contains randomized components, including general company information, key financial indicators (such as revenues and profits), team characteristics, and measures of social impact. By fully randomizing these attributes, we isolate the marginal effect of social impact information relative to other firm characteristics. Although we designed the company profiles to appear realistic, respondents are explicitly informed that the investment opportunities are purely hypothetical, ensuring no deception.

Eliciting truthful preferences requires meaningful incentives. For investors recruited through LinkedIn and professional networks, we achieve this by informing respondents that their survey evaluations will be used to facilitate introductions with startups from Villgro's incubation programs that are actively seeking capital. Using the preferences revealed in the survey, we identify potential matches between participating investors and eligible startups and facilitate email introductions.

Participation in this matchmaking process is entirely optional, and respondents could choose to complete the survey without being connected to any startups.

B. Investor Sample and Recruitment

Our recruitment specifically targeted early-stage investors based in India with demonstrated experience investing in India-based startups. To reach this group, we recruited investors through multiple channels.

The primary recruitment channel involved identifying angel investors through LinkedIn—using data provided by Revelio Labs—and reaching additional qualified respondents via personal and professional networks at Harvard Business School and Villgro. To further broaden our sample, we also partnered with Dynata, a survey platform that allowed us to connect with a wider set of potential early-stage investors. Prior experience in social impact investing was not required. Invitations were therefore designed to appeal to a wide range of investors while clearly communicating the survey's objective of understanding preferences for social enterprises.

These combined efforts yielded a total of 223 participants—65 recruited through the primary channels and 158 via Dynata. This recruitment strategy contributed to meaningful variation in investment experience, capital deployment, and sectoral focus. On average, participants reported having made 19.7 private investments, including 13 investments in India-based startups. Among the LinkedIn sample for which dollar values were collected, median total capital invested was $2 million, with median capital invested in India at $1 million. Typical check sizes ranged widely, from under $25,000 to over $5 million, with the most common ranges being $25–50k (15.2%) and $500k–1M (15.2%).[5] Our sample demonstrates substantial engagement with impact investing. The vast majority of participants (86.6%) reported considering social or environmental impact when evaluating investments, with over half (53.4%) considering both social and environmental dimensions. Furthermore, 77.1% indicated willingness to accept below-market returns in pursuit of impact objectives, and nearly 90% reported measuring impact in their portfolio companies either always or when possible. These characteristics indicate that our sample captures investors who are not only experienced in early-stage investing but also actively engaged with the impact investing landscape. Tables 3 and 4 provide detailed summaries of all investor characteristics and preferences.

C. Survey Structure

The survey begins with an overview of its goals, incentives to participate, and a confirmation of consent to proceed.[6]

[5]See Online Appendix Figure B2 for a comparison of check size distributions between recruitment channels.

[6]Participants recruited through the primary channel (LinkedIn and professional networks) were informed about the matchmaking incentive described in Section A. The survey was conducted using the Qualtrics platform.

The survey consists of two main sections. The first section collects baseline information on the backgrounds and investment approaches of the respondents. These questions cover broad areas such as prior investment experience, typical check size, and preferred sectors. This section provides both background context and a screening mechanism to ensure that only investors with an active interest in India-based startups continue.

The second section constitutes the core experimental exercise, designed to elicit investors' preferences for social enterprises and identify the causal effect of social impact information on investment decisions. Respondents are asked to evaluate 15 anonymized company profiles that vary systematically across multiple dimensions—including financial performance, team characteristics, and social impact metrics. Before beginning the evaluation task, we provide participants with a definition of customer surplus, including examples, and explicitly note that some companies may signal their social impact in their profiles. For each profile, participants then indicate their level of investment interest and the likelihood they would request additional information. The survey concludes with a short set of feedback questions.

D. Company Profiles: Construction and Experimental Design

D.1. *Profile Randomization.* To construct the synthetic company profiles, we first analyzed firms participating in Villgro's incubation program to identify the key characteristics of real India-based social enterprises. This analysis drew on detailed firm-level data collected through our surveys and was supplemented with information from company websites and public materials provided by Villgro. We then examined multiple external platforms—including Crunchbase, PitchBook, and their India-focused counterparts—to study how such firms are typically presented to investors. Based on this review, we identified the principal components commonly featured in company profiles and the typical language used to describe them.

Table A5 summarizes the full set of randomized profile components, organized into four categories: (i) company information (e.g., headquarters location, industry, year of incorporation, business model); (ii) key financials (e.g., number of investors, customers, employees, capital raised, revenues, profits); (iii) team characteristics (e.g., team size, founder roles, education); and (iv) social impact metrics (e.g., average customer surplus, customer income, percentage of customers earning less than $5 per day). For each component, the table reports the number of possible values, the probability distribution over options, and any restrictions that ensure internal consistency across profile attributes. Profile generation proceeds by independently randomizing each component according to these probabilities.[7] To ensure realistic profiles, we impose logical restrictions between components. These restrictions, detailed in the final column of Table A5, guarantee that generated

[7]For example, the Primary Industry component comprises seven mutually exclusive options. For each synthetic profile, we draw a single option at random; the probabilities in parentheses give the unconditional chance that each option is selected: Agri-Business (28%), Health & Health Services (23%), Energy & Cleantech (15%), Education & Skill Development (15%), Waste Management (9%), E-Commerce (5%), and Biotechtech (5%).

profiles represent plausible companies. We further conducted a detailed manual review of a random sample of generated profiles to verify their realism before deploying the survey.

D.2. *Profile Design and Social Impact Treatments.* All profiles follow the same structure, organized into three broad categories: (i) general company information, such as headquarters location and sector; (ii) team characteristics, including founder education; and (iii) key financials, such as revenues, profits, and number of investors.

Each profile also includes a *Social Impact* section, which constitutes the primary dimension of interest and varies systematically across profiles. All profiles display baseline customer demographics—average monthly income per customer and the percentage of customers earning less than $5 per day. Depending on the experimental condition, the Social Impact section may include only these baseline measures (Type I; see Figure 3), an additional qualitative statement summarizing the firm's social impact (Type II), total customer surplus (Type III), or total customer surplus along with average customer surplus and average customer surplus expressed as a percentage of household income (Type IV). Figure 4 illustrates the Social Impact section for each of these treatment conditions (Types II–IV).[8] For Types III and IV, a color-coded sidebar indicates whether the firm's total customer surplus falls above or below the median of the synthetic company sample. Respondents were guided on the definition of social impact measures before beginning the experiment and could review definitions of all profile components throughout the rating exercise via a glossary button. Importantly, the inclusion and type of social impact information were randomized independently of other company characteristics, allowing us to isolate the causal effect of social impact signals on investors' evaluations.

E. Rating Company Profiles

To elicit investors' preferences, respondents were asked to evaluate a randomly assigned set of 15 synthetic company profiles. For each profile, investors reported their level of investment interest using a 7-point Likert scale. The primary outcome is based on responses to the following question:

> "How interested would you be in investing in this company?"

The scale ranges from 1 ("I'm not at all interested in investing in this company") to 7 ("I am very interested in this company; it stands out as a strong candidate for investment"). To provide clarity and encourage consistent use of the scale, we included explicit anchors: a rating of 1 indicates no interest, ratings of 2–3 indicate low interest, ratings of 4–6 indicate moderate interest, and a rating

[8]To construct the qualitative impact statements, we leveraged the impact descriptions provided by Villgro-incubated firms in our surveys, where they were asked to describe their social or environmental impact in their own words. We then used large language models (LLMs) to generate similar statements that replicate the tone, length, and content patterns observed in these real examples, ensuring consistency and realism across synthetic profiles.

of 7 reflects high interest. Respondents were instructed to use the full range of the scale when evaluating the profiles.[9]

At the respondent level, the 15 profiles were randomized to ensure a balanced exposure across different social impact types (see Section D.2). Specifically, each respondent evaluated 6 profiles with customer surplus (either Type III or Type IV), 6 profiles with no customer surplus (Type I), and 3 profiles containing a qualitative social impact narratives (Type II).[10] This design allows us to isolate the effects of different types of social impact information on investment interest while controlling for other profile characteristics.

F. Estimating Preferences for Company Attributes

To examine whether early-stage investors are responsive to social impact information, we estimate the causal effect of displaying customer surplus metrics on investment interest. Our empirical strategy exploits the independent randomization of all profile attributes to identify how different forms of social impact information—quantitative metrics versus qualitative statements—affect investor evaluations. We distinguish between profiles displaying customer surplus (CS) below versus above the median of the generated company sample. This distinction allows us to separately identify investor responses to relatively low versus relatively high social impact performance. We also include an indicator for whether the profile contains a qualitative social impact statement, enabling us to disentangle the effects of qualitative versus quantitative social impact disclosure. Section D.2 provides details on these treatment variations.

We formalize this approach with the following linear model:

$$y_{ij} = \alpha_i + \phi_j + \beta_{CS_L} \cdot CS_{L,j} + \beta_{CS_H} \cdot CS_{H,j} + \beta_S \cdot S_j + \sum_{k=1}^{K} \theta_k X_{jk} + \varepsilon_{ij}, \tag{III.1}$$

where y_{ij} is the investment interest of respondent i in profile j, α_i are respondent fixed effects, and ϕ_j are profile fixed effects. $CS_{L,j}$ and $CS_{H,j}$ indicate whether the profile's customer surplus is below or above the median (conditional on being shown), and S_j indicates whether the profile includes a qualitative social impact sentence. The variable X_{jk} is an indicator equal to one if characteristic k takes a specific value or meets a specified threshold in profile j (e.g., "Profitable Firm", "High Revenues", "No Investors"), and zero otherwise. There are K such characteristics, detailed in Table A6, and they are constructed from the randomized profile components described

[9] To encourage thoughtful and differentiated responses, investors who assigned identical ratings to the first five profiles received an automated prompt encouraging greater variation in their evaluations. For the subset of respondents participating in the startup matchmaking process, we emphasized the importance of using the full scale to facilitate accurate matches between their stated preferences and available investment opportunities.

[10] At the respondent level, participants had a 50% probability of being assigned to view customer-surplus profiles of Type III and a 50% probability of viewing customer-surplus profiles of Type IV.

in Section D.1. The parameters θ_k capture the effects of these additional profile characteristics. We use heteroscedasticity-consistent (robust) standard errors (Abadie et al., 2023).

G. Results

Table 5 presents the regression results examining how investors' interest varies with the company characteristics and social impact information displayed. The dependent variable, *Investment Interest*, captures investors' level of interest in the company on a 1–7 scale.

Profiles with stronger financial indicators receive significantly higher ratings, indicating that respondents attend closely to traditional signals: profitable firms command a premium of approximately 0.56–0.61 scale points, while high-revenue firms receive ratings 0.28–0.30 points higher. Conversely, profiles with no existing investors receive significantly lower ratings (0.14–0.17 points), suggesting that investors view the presence of other backers as a positive signal. Firm size and capital raised show no association with investment interest.

Across all specifications, we find strong evidence that investors systematically respond to the presence and magnitude of quantified social impact information. Profiles reporting customer surplus above the median are associated with 0.37–0.42 higher ratings, while those reporting below-median customer surplus receive 0.36–0.40 lower ratings. Both effects are large and statistically significant at the 1% level across all columns. By contrast, the inclusion of a qualitative social impact statement has a small and statistically insignificant effect on investors' interest, suggesting that quantitative evidence of impact carries greater weight than qualitative descriptions. These patterns are robust across specifications that sequentially add respondent fixed effects (Column 2), profile fixed effects (Column 3), and both sets of fixed effects simultaneously (Column 4). Appendix Table A7 reports analogous regressions using continuous measures of customer surplus and income rather than median-based indicators. The results are consistent: investors respond positively to higher levels of customer surplus, and the magnitudes align closely with those observed in the main specifications.

IV. Discussion

This paper provides experimental evidence on the impact of introducing rigorous impact metrics to high-growth social enterprises and investors. Firms that received hands-on support to operationalize impact measurement frameworks experienced faster revenue growth and raised more capital. Investors utilized quantified impact metrics to differentiate between early stage startups, but largely ignored qualitative impact statements.

Our results strongly suggest that the social enterprise and impact investing sectors would benefit from standardized, rigorous impact metrics, yet we have little to say about the mechanisms that drive our results. Do firms generate more revenue because they learn about what their customers value? Do impact measurement capabilities have spillovers onto other management practices?

More concerningly, might firms be learning about the demand curve they face and raising prices to generate revenue? What signal do investors draw from impact metrics? Are investors drawing inference about future demand and profitability, or do they place intrinsic value on impact? We hope future research will shed light on these questions.

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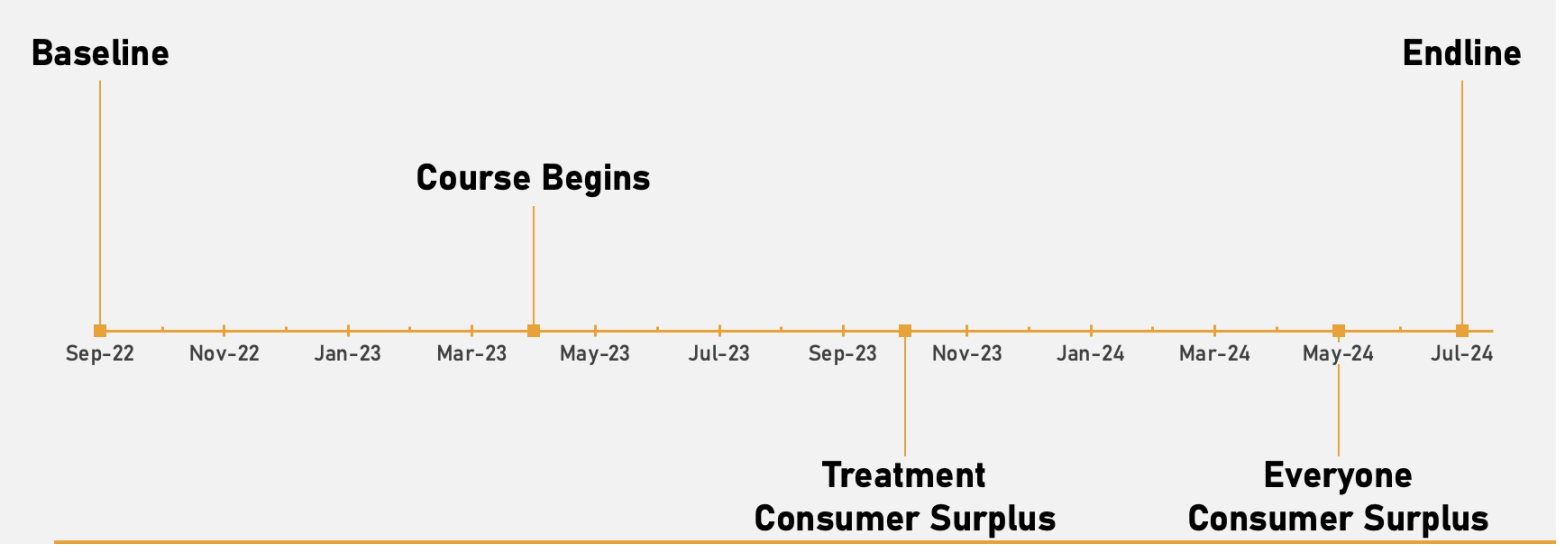
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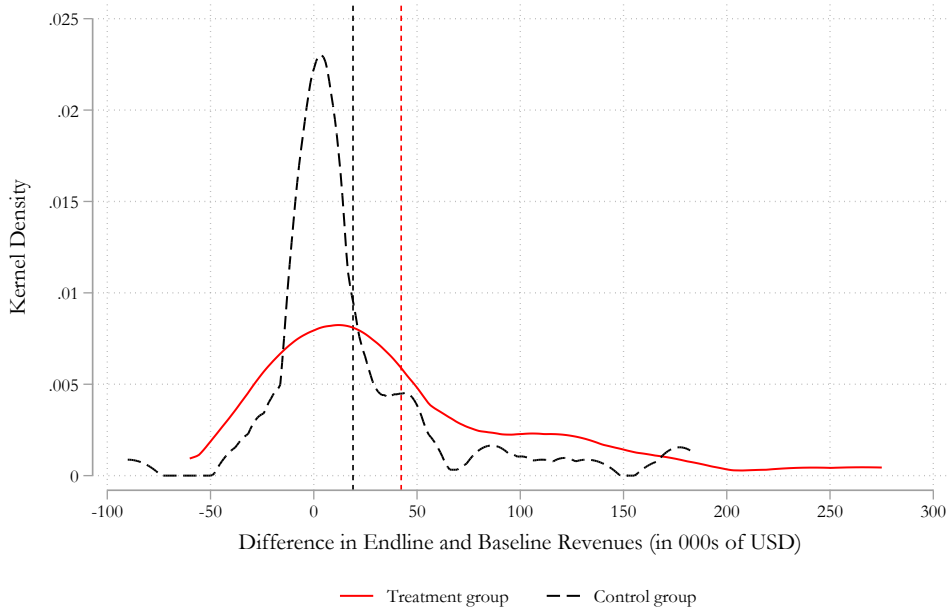
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FIGURE 1. Study Timeline

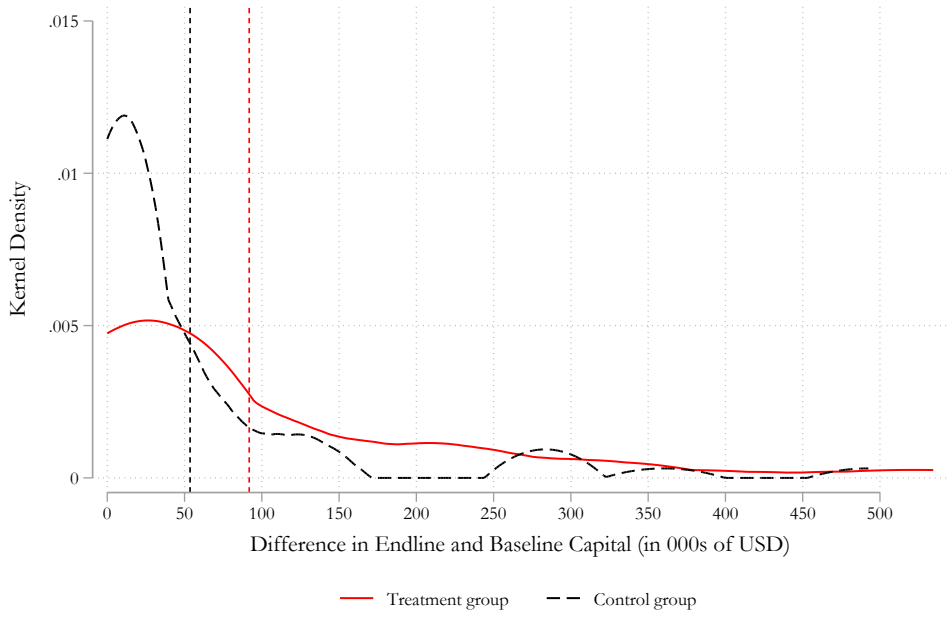


Notes: This figure illustrates the timeline of the randomized controlled trial. ADD MORE

FIGURE 2. Difference Between Endline and Baseline Revenues and Capital



Panel A: Revenues



Panel B: Capital

Notes: The figure presents kernel densities of the difference between endline and baseline values of revenues and capital. Values are top-coded at the 95th percentile. There are 110 firms in Panel A and 120 in Panel B (the difference is due to missing data on revenues).

FIGURE 3. Example Company Profile (Baseline)

KaraVolt

About the Company

The company focuses on the development and operation of smart grid technologies that enhance the efficiency and reliability of renewable energy integration. Their solutions allow for the real-time monitoring of energy production and consumption, enabling better management of grid stability. Its systems empower cities and municipalities to transition smoothly towards renewable energy while reducing transmission losses.

Company Information

Headquarter:	Mumbai, Maharashtra
Primary Industry:	Energy & Cleantech
Sub Industry:	Renewable Energy
Target Market:	Urban Consumers
Incorporation Year:	2017
Business Model:	Social Impact Hybrid Model
Type of Buyer:	Primarily Businesses

Key Financials

No. Investors:	1	**Total capital raised:**	$ 104.0 K (₹ 86.6 L)
No. Customers:	500	**Revenues in 2024:**	$ 12.1 K (₹ 10.1 L)
No. Employees:	35	**Profits in 2024:**	$ 2.7 K (₹ 2.3 L)

Social Impact

Average monthly income per customer:	$ 3.1 K (₹ 2.5 L)
% of customers earning less than $5/day:	0 %

Team

Founder & CEO:	Bachelor of Science in Economics

Notes: This figure shows an example of a synthetic company profile used in the survey experiment (Type I). Each profile contains general company information (headquarters, sector), team characteristics (founder education), and key financials (revenues, profits, number of investors). The Social Impact section displays baseline customer demographics: average monthly income per customer and the percentage of customers earning less than $5 per day. This baseline profile (Type I) contains no additional impact signal beyond these demographic measures. Alternative treatments add either a qualitative impact statement (Type II) or quantitative customer surplus metrics (Types III–IV) to this section; see Figure 4.

FIGURE 4. Social Impact Signal Treatments

Social Impact

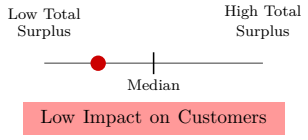
Average monthly income per customer:	$ 494	(₹ 41,102)
% of customers earning less than $5/day:	11-20	%

Impact Overview: The company has significantly reduced environmental impact by supplying biodegradable hospital-grade cleaning products, supporting healthcare facilities in adopting eco-friendly practices. This has contributed to a noticeable reduction in waste and improved sustainability in healthcare environments.

Panel A: Qualitative Statement (Type II)

Social Impact

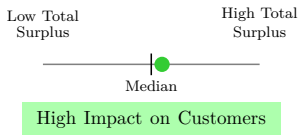
Average monthly income per customer:	$ 1.3 K	(₹ 1.1 L)
% of customers earning less than $5/day:	0	%
Total customer surplus:	$ 16	(₹ 1,372)



Panel B: Total Customer Surplus (Type III)

Social Impact

Average monthly income per customer:	$ 1.0 K	(₹ 86,010)
% of customers earning less than $5/day:	0-10	%
Average customer surplus:	$ 22	(₹ 1,823)
Average customer surplus (% of income):	1.5	%
Total customer surplus:	$ 996	(₹ 82,958)



Panel C: Total and Average Customer Surplus (Type IV)

Notes: This figure displays the three Social Impact section variants used in the survey experiment. Panel A shows a qualitative statement describing the firm's social impact (Type II). Panel B presents total customer surplus only (Type III). Panel C presents total customer surplus, average customer surplus, and average customer surplus as a percentage of income (Type IV). Profiles with no social impact section (Type I) are not shown. The color-coded sidebar indicates whether the firm's total customer surplus falls above (green) or below (red) the median of the synthetic company sample. All other profile sections remain identical across treatments; see Figure 3 for the baseline profile structure.

TABLE 1. Randomization Check

	Control	Treatment	
	Mean	Mean	Difference
	(1)	(2)	(3)
Panel A: Borrower Characteristics			
Firm Age (Years)	5.154	5.387	0.233
	[4.197]	[2.809]	(0.580)
Firm Stage = Minimum Viable Product	0.265	0.262	-0.003
	[0.444]	[0.443]	(0.069)
Firm Stage = Launched in Market	0.337	0.300	-0.037
	[0.476]	[0.461]	(0.073)
Firm Stage = Growth Stage	0.398	0.438	0.040
	[0.492]	[0.499]	(0.078)
B2C	0.458	0.412	-0.045
	[0.501]	[0.495]	(0.078)
Sector = Agri-Business	0.265	0.262	-0.003
	[0.444]	[0.443]	(0.069)
Sector = Health Services and Tech	0.253	0.200	-0.053
	[0.437]	[0.403]	(0.066)
Sector = Energy and Clean-tech	0.157	0.275	0.118*
	[0.366]	[0.449]	(0.064)
Sector = Education	0.060	0.087	0.027
	[0.239]	[0.284]	(0.041)
Sector = Livelihoods and Skills	0.181	0.100	-0.081
	[0.387]	[0.302]	(0.055)
Revenues FY '21-'22 (in 000s USD)	75.562	75.117	-0.446
	[145.847]	[149.584]	(23.885)
Number of Employees	11.948	13.307	1.359
	[16.038]	[17.810]	(2.747)
Capital Raised (in 000s USD)	125.387	134.397	9.010
	[324.605]	[417.842]	(60.358)
Number of Investors	3.052	2.127	-0.925
	[9.543]	[2.932]	(1.181)
P-Value for Joint Difference F test:			0.834
Observations	83	80	163

Notes: Notes: In this table we present the baseline characteristics of firms by treatment assignment. Column 1 shows the mean of the variable for the control group, column 2 shows the mean for the treatment group, and column 3 is the difference between column 2 and column 1. For conciseness, we omit the the residual business sector from the table.

TABLE 2. The Effect of Treatment on Financial Outcomes of Firms

	Revenues		Profits > 0		Total Capital Raised	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	23.94***	23.35***	0.19***	0.16**	37.89***	39.64***
	(6.13)	(5.83)	(0.07)	(0.07)	(10.41)	(10.44)
	{0.000}	{0.000}	{0.009}	{0.019}	{0.000}	{0.000}
Post * Treat	17.40*	20.21**	-0.04	-0.01	44.87**	43.11**
	(9.38)	(9.28)	(0.09)	(0.09)	(19.09)	(19.07)
	{0.062}	{0.031}	{0.635}	{0.879}	{0.022}	{0.028}
Control Pre Mean:	44.55	44.55	0.36	0.36	75.11	75.11
	[83.29]	[83.29]	[0.48]	[0.48]	[142.50]	[142.50]
N. Obs	443	443	421	421	241	241
N. Firms	120	120	121	121	121	121
Firm FE	No	Yes	No	Yes	No	Yes

Notes: In this table we present estimated treatment effects on revenues (in 000s USD), whether the firm has reached profitability, and total capital raised (in 000s USD). The odd columns implement regression specification II.1. The coefficient on treatment is not shown in the table but included in the regressions. The even columns include a firm fixed effect. For revenues and profits, we could have up to 4 observations per firm. We have fewer than that because of missing data or if a firm had not yet incorporated in that year. We only ask about capital raised at baseline and capital raised to date at endline. We drop 4 observations from the analysis: there are 4 firms with baseline revenues about USD 1 million. All values are top-coded at the 95th percentile. Standard errors are clustered at the firm level. Wildbootstrap p-values are shown in curly brackets. * p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01.

TABLE 3. Summary Statistics: Investment Experience

	N	Mean	SD	P25	Median	P75	P95
Total private investments	223	19.7	44.4	5.0	8	12	81.8
Investments in India	223	13.0	27.1	3.0	5	8	59.0
Total capital invested (USD millions)†	65	69.7	263.9	0.4	2	50	100.0
Capital invested in India (USD millions)†	65	47.9	156.9	0.2	1	25	100.0

Note: Sample consists of 223 early-stage investors recruited via LinkedIn (N = 65) and Dynata (N = 158). †Dollar values available only for LinkedIn sample.

TABLE 4. Summary Statistics: Investment Preferences

	N	%
Panel A: Typical check size (USD)		
<25k	21	9.4
25–50k	34	15.2
50–100k	26	11.7
100–250k	30	13.5
250–500k	33	14.8
500k–1M	34	15.2
1–5M	24	10.8
>5M	21	9.4
Panel B: Consider impact when evaluating investments		
Both social and environmental	119	53.4
Primarily social	74	33.2
Primarily environmental	9	4
No	21	9.4
Panel C: Willing to accept below-market returns		
Yes	172	77.1
No	51	22.9
Panel D: Measure impact of portfolio companies		
Yes, always	105	47.1
Yes, when possible	95	42.6
No	23	10.3
Panel E: Challenges in impact investing‡		
Balancing returns with impact	137	27.8
Lack of standardized data/measurement	111	22.5
Higher costs and complexity in diligence	104	21.1
Difficulty assessing and comparing impact	111	22.5
No systematic challenges	9	1.8
Do not consider impact investments	15	3
Panel F: Industry preferences (top 5)‡		
Financial Technology	114	9.2
Healthcare & Biotech	95	7.6
E-Commerce	86	6.9
Financial Services	84	6.7
Energy	83	6.7

Note: Sample consists of 223 early-stage investors recruited via LinkedIn (N = 65) and Dynata (N = 158). ‡Multi-select questions; percentages calculated over total selections.

TABLE 5. Investment interest and company characteristics

	Investment Interest			
	(1)	(2)	(3)	(4)
Impact sentence Displayed [0/1=Yes]	0.093	0.097	0.096	0.107
	(0.08)	(0.07)	(0.08)	(0.07)
CS Below Median [0/1=Yes]	-0.372***	-0.401***	-0.356***	-0.393***
	(0.09)	(0.07)	(0.09)	(0.07)
CS Above Median [0/1=Yes]	0.374***	0.420***	0.371***	0.419***
	(0.09)	(0.07)	(0.10)	(0.08)
High nr. customers [0/1=Yes]	0.057	0.062		
	(0.07)	(0.06)		
Young Firm [0/1=Yes]	-0.093	0.018		
	(0.06)	(0.05)		
Profitable Firm [0/1=Yes]	0.607***	0.560***		
	(0.08)	(0.06)		
Large Firm [0/1=Yes]	0.003	-0.002		
	(0.07)	(0.06)		
High Revenues [0/1=Yes]	0.295***	0.280***		
	(0.06)	(0.05)		
High Capital Raised [0/1=Yes]	-0.051	-0.062		
	(0.07)	(0.06)		
No Investors [0/1=Yes]	-0.172**	-0.143**		
	(0.07)	(0.06)		
Observations	3,345	3,345	3,345	3,345
Mean	4.45	4.45	4.45	4.45
Unique Investors	223	223	223	223
Respondent FEs	No	Yes	No	Yes
Profile FEs	No	No	Yes	Yes
R^2	0.055	0.438	0.114	0.487
Adjusted R^2	0.053	0.396	0.064	0.417

Notes: This table reports the coefficients of OLS regressions estimating the effect of whether a quantitative surplus measure or an impact sentence was displayed in the rated profile. The variable *CS Above Median* is a dummy indicator that takes the value of 1 if the total customer surplus is above the median, and 0 otherwise. *Investment Interest* is on a scale of 1-7. Column (1) shows the baseline OLS. Column (2) shows the regressions adding respondent fixed effects. Column (3) shows the regressions adding profile fixed effects. Column (4) shows the regressions adding profile and respondent fixed effects. We report robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Supplemental Appendix for "Measuring the Impact of Impact Measurement"

A. Additional Tables

TABLE A1. Large Firm Baseline Differences

	Main Sample	Large Firms	
	Mean	Mean	Difference
	(1)	(2)	(3)
Panel A: Borrower Characteristics			
Firm Age (Years)	5.268	7.750	2.482
	[3.574]	[3.862]	(1.813)
Firm Stage = Minimum Viable Product	0.264	0.000	-0.264
	[0.442]	[0.000]	(0.222)
Firm Stage = Launched in Market	0.319	0.000	-0.319
	[0.468]	[0.000]	(0.234)
Firm Stage = Growth Stage	0.417	1.000	0.583**
	[0.495]	[0.000]	(0.248)
B2C	0.436	0.250	-0.186
	[0.497]	[0.500]	(0.252)
Sector = Agri-Business	0.264	0.000	-0.264
	[0.442]	[0.000]	(0.222)
Sector = Health Services and Tech	0.227	0.250	0.023
	[0.420]	[0.500]	(0.213)
Sector = Energy and Clean-tech	0.215	0.250	0.035
	[0.412]	[0.500]	(0.209)
Sector = Education	0.074	0.000	-0.074
	[0.262]	[0.000]	(0.131)
Sector = Livelihoods and Skills	0.141	0.250	0.109
	[0.349]	[0.500]	(0.178)
Revenues FY '21-'22 (in 000s USD)	75.344	2455.897	2380.553***
	[147.204]	[1360.903]	(121.025)
Number of Employees	12.618	173.750	161.132***
	[16.893]	[146.721]	(13.394)
Capital Raised (in 000s USD)	129.803	34.433	-95.371
	[372.017]	[59.639]	(215.503)
Number of Investors	2.608	1.000	-1.608
	[7.169]	[1.155]	(3.597)
P-Value for Joint Difference F test:			0.000
Observations	163	4	167

Notes: Notes: In this table we present the baseline characteristics of all firms compared to firms with baseline revenues in excess of USD 1 million. Column 1 shows the mean of the main sample, column 2 shows the mean for the 4 large firms, and column 3 is the difference between column 2 and column 1. For conciseness, we omit the the residual business sector from the table.

TABLE A2. Attrition Check

	Control	Treatment	
	Mean	Mean	Difference
	(1)	(2)	(3)
Panel A: Borrower Characteristics			
Firm Age (Years)	5.167	5.412	0.245
	[2.854]	[2.717]	(0.943)
Firm Stage = Minimum Viable Product	0.286	0.381	0.095
	[0.463]	[0.498]	(0.148)
Firm Stage = Launched in Market	0.238	0.333	0.095
	[0.436]	[0.483]	(0.142)
Firm Stage = Growth Stage	0.476	0.286	-0.190
	[0.512]	[0.463]	(0.151)
B2C	0.571	0.381	-0.190
	[0.507]	[0.498]	(0.155)
Sector = Agri-Business	0.143	0.190	0.048
	[0.359]	[0.402]	(0.118)
Sector = Health Services and Tech	0.333	0.238	-0.095
	[0.483]	[0.436]	(0.142)
Sector = Energy and Clean-tech	0.190	0.286	0.095
	[0.402]	[0.463]	(0.134)
Sector = Education	0.048	0.143	0.095
	[0.218]	[0.359]	(0.092)
Sector = Livelihoods and Skills	0.190	0.143	-0.048
	[0.402]	[0.359]	(0.118)
Revenues FY '21-'22 (in 000s USD)	153.634	118.807	-34.827
	[220.255]	[267.885]	(82.693)
Number of Employees	19.944	18.176	-1.768
	[24.666]	[30.627]	(9.374)
Capital Raised (in 000s USD)	200.492	333.543	133.051
	[475.684]	[864.707]	(240.964)
Number of Investors	2.333	2.000	-0.333
	[2.521]	[4.062]	(1.136)
P-Value for Joint Difference F test:			0.502
Observations	21	21	42

Notes: Notes: In this table we present the baseline characteristics of firms that did not answer the endline survey by treatment assignment. Column 1 shows the mean of the variable for the control group, column 2 shows the mean for the treatment group, and column 3 is the difference between column 2 and column 1. For conciseness, we omit the the residual business sector from the table.

TABLE A3. The Effect of Treatment on Financial Outcomes of Firms

	Revenues		Profits > 0		Total Capital Raised	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	32.55***	31.79***	0.19***	0.16**	63.08***	65.73***
	(10.57)	(10.30)	(0.07)	(0.07)	(23.29)	(23.59)
	{0.001}	{0.001}	{0.009}	{0.019}	{0.000}	{0.000}
Post * Treat	24.06	27.61*	-0.04	-0.01	28.34	25.69
	(14.87)	(14.99)	(0.09)	(0.09)	(30.22)	(30.43)
	{0.104}	{0.066}	{0.635}	{0.879}	{0.367}	{0.419}
Control Pre Mean:	51.03	51.03	0.36	0.36	104.46	104.46
	[109.67]	[109.67]	[0.48]	[0.48]	[269.89]	[269.89]
N. Obs	443	443	421	421	241	241
N. Firms	120	120	121	121	121	121
Firm FE	No	Yes	No	Yes	No	Yes

Notes: In this table we present estimated treatment effects on revenues (in 000s USD), whether the firm has reached profitability, and total capital raised (in 000s USD). The odd columns implement regression specification II.1. The coefficient on treatment is not shown in the table but included in the regressions. The even columns include a firm fixed effect. For revenues and profits, we could have up to 4 observations per firm. We have fewer than that because of missing data or if a firm had not yet incorporated in that year. We only ask about capital raised at baseline and capital raised to date at endline. We drop 4 observations from the analysis: there are 4 firms with baseline revenues about USD 1 million. All values are top-coded at the 99th percentile. Standard errors are clustered at the firm level. Wildbootstrap p-values are shown in curly brackets. * p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01.

TABLE A4. The Effect of Treatment on Fundarising Outcomes of Firms

	Equity		Debt		Grant	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	5.99***	6.55***	5.55**	5.80**	15.47***	16.09***
	(2.10)	(2.05)	(2.35)	(2.37)	(4.64)	(4.66)
	{0.001}	{0.000}	{0.005}	{0.002}	{0.000}	{0.000}
Post * Treat	18.58**	18.03**	10.11**	9.86**	11.19	10.56
	(8.06)	(8.03)	(4.76)	(4.76)	(8.26)	(8.26)
	{0.016}	{0.021}	{0.033}	{0.038}	{0.181}	{0.210}
Control Pre Mean:	27.70	27.70	9.74	9.74	28.51	28.51
	[76.39]	[76.39]	[26.64]	[26.64]	[61.16]	[61.16]
N. Obs	241	241	241	241	241	241
N. Firms	121	121	121	121	121	121
Firm FE	No	Yes	No	Yes	No	Yes

Notes: In this table we present estimated treatment effects equity, debt, and grant capital raised (measured in 000s of USD). The odd columns implement regression specification II.1. The coefficient on treatment is not shown in the table but included in the regressions. The even columns include a firm fixed effect. We drop 4 observations from the analysis: there are 4 firms with baseline revenues about USD 1 million. All USD values are top-coded at the 95th percentile. Standard errors are clustered at the firm level. Wildbootstrap p-values are shown in curly brackets. * p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01.

TABLE A5. Synthetic Company Profile Components

Variable (Probability)	N	Options (Probability)	Restrictions
Panel A: Company Information			
Headquarters City (1.0)	11	Mumbai/Pune/Navi Mumbai (0.26); Bangalore (0.15); Chennai (0.10); Noida/Gurgaon/Delhi NCR (0.20); Hyderabad (0.12); Bhubaneshwar (0.05); Jaipur/Udaipur/Jodhpur (0.05); Gurgaon (0.05); Thiruvananthapuram/Trivandrum/Alappuzha/Calicut (0.05)	State is selected conditional on the chosen city.
Headquarters State (1.0)	11	Maharashtra (0.25); Karnataka (0.15); Tamil Nadu (0.10); Uttar Pradesh (0.12); Telangana (0.12); Delhi (0.06); Odisha (0.05); Rajasthan (0.05); Haryana (0.05); Kerala (0.05)	Acts as a dummy variable; does not directly influence the pooling of states.
Primary Industry (1.0)	7	Agri-Business (0.28); Health & Health Services (0.23); Energy & Cleantech (0.15); Education & Skill Development (0.15); Waste Management (0.09); E-Commerce (0.05); Biotechtech (0.05)	—
Sub-Industry (1.0)	10	Farm Equipment/Organic Food/Sustainable Agri-Inputs (0.23); Maternal & Fetal Care/Eco-friendly Hygiene/Personal Care/Medical Equipment (0.23); Renewable Energy/Solar Panel Technology/Electric Mobility (0.15); Digital Learning/Platform/Employment & Professional Development (0.15); Water Management/Waste Management & Repurposing (0.08); Sustainable Retail Products (0.05); Housing & Construction (0.05)	Sub-categories are selected conditionally based on Primary Industry.
Target Group (1.0)	6	Farmers (0.09); Urban Consumers (0.09); Women (0.09); Schools in rural and urban segments/B2B (0.06); BOP/B2B/Urban Consumers/Rural Consumers (0.82); Generic (default)	Default is "Generic". If Primary Industry is Agri-Business, Health, E-Commerce, or Education, target group is replaced by the corresponding category. If Primary Industry is Health and Sub-Industry is Medical Equipment, target group is set to "Health > B2B".
Year of Incorporation (1.0)	3	2010–2016 (0.29); 2017–2019 (0.50); 2021–2024 (0.30)	—
Business Model (1.0)	3	For-profit Organization (0.80); Non-profit Organization (0.10); Social Impact Hybrid Model (0.10)	—

Continued on next page

Table A5 (continued)

Variable (Probability)	N	Options (Probability)	Restrictions
Type of Buyer (1.0)	4	Primarily Government (0.05); Primarily Businesses (0.46); Primarily Individuals (0.35); Mixed Buyers (0.14)	—
Panel B: Key Financials			
Number of Investors (1.0)	5	0 (0.30); 1 (0.25); 2–3 (0.26); 4–5 (0.11); 6–11 (0.09)	If Year of Incorporation is after 2024, capped at 5 investors. If Total Capital Raised > 0, then Number of Investors > 0.
Number of Customers (1.0)	8	1–10 (0.18); 11–50 (0.18); 51–100 (0.12); 101–500 (0.20); 501–1,000 (0.03); 1,001–10,000 (0.15); 10,001–30,000 (0.15)	If Revenues < $60k, capped at 501–1,000 customers. If Year of Incorporation is after 2024, capped at 500 customers.
Number of Employees (1.0)	7	1 (0.07); 2–5 (0.30); 6–10 (0.20); 11–30 (0.23); 31–50 (0.10); 51–100 (0.05); 101–500 (0.05)	If Year of Incorporation is after 2024, capped at 50 employees. If Revenues < $10k, capped at 10 employees.
Total Capital Raised (1.0)	9	$0 (0.10); $0–10k (0.10); $10–30k (0.12); $30–60k (0.14); $60–120k (0.10); $120–240k (0.20); $240–500k (0.12); $500k–1.5M (0.12)	Values displayed in both USD and INR. If Year of Incorporation is 2023 or 2024, capped at $120k. If Number of Investors = 0, then Total Capital Raised = 0.
Revenues (1.0)	7	$1–10k (0.20); $10–30k (0.20); $30–60k (0.15); $60–120k (0.10); $120–300k (0.10); $300–600k (0.10); $600k–1.5M (0.05)	Values displayed in both USD and INR. If Year of Incorporation is after 2024, capped at $120k. If Total Capital Raised = 0, then Revenues ≤ $300k.
Profits (1.0)	8	Negative (0.18); $0 (0.06); $0–1k (0.03); $1–5k (0.10); $5–10k (0.22); $10–20k (0.12); $20–60k (0.10); $60–120k (0.10)	Values displayed in both USD and INR. Distribution shown applies when Revenues ≤ $120k. For higher revenues, profits follow a different distribution ensuring Revenues always exceed Profits.
Panel C: Team			
Team Size (1.0)	3	1 founder (0.40); 2 founders (0.40); 3 founders (0.20)	—
Founder 1 Role (1.0)	3	Founder & CEO (0.33); Founder (0.33); Co-Founder (0.33)	—
Founder 2 Role (1.0)	5	Co-Founder (0.50); CFO/CEO/COO/CTO (0.25); Co-Founder & CTO/CFO (0.25)	Shown only if Team Size ≥ 2.

Continued on next page

Table A5 (continued)

Variable (Probability)	N	Options (Probability)	Restrictions
Founder 3 Role (1.0)	2	Co-Founder (0.80); Co-Founder & COO/CTO/CFO (0.20)	Shown only if Team Size = 3.
Founder Education (1.0)	4	Undergraduate (0.35); Master's degree (MSc/MTech/IIT) (0.35); MBA (IMBA/IIM/INSEAD/Kellogg) (0.20); PhD (0.10)	All founders are assigned the same education tier.
Panel D: Social Impact			
Average Customer Surplus (1.0)	10	\$0 (0.17); \$0–2 (0.12); \$2–5 (0.15); \$5–10 (0.11); \$10–25 (0.17); \$25–50 (0.11); \$50–100 (0.11); \$100–250 (0.04); \$250–500 (0.02)	Values displayed in both USD and INR.
Average Monthly Income (1.0)	6	\$100–200 (0.06); \$200–500 (0.13); \$500–1k (0.34); \$1–1.5k (0.40); \$1.5–2k (0.30); \$2–4.5k (0.12)	—
Average Number of Transactions (1.0)	5	0.1–2 (0.40); 1–2 (0.25); 2–5 (0.15); 3–5 (0.10); 4–7.5 (0.10)	—
Customer Surplus as % of Income (1.0)	4	0–5% (0.40); 5–10% (0.30); 10–20% (0.20); 20–30% (0.10)	Shown only if Average Customer Surplus > 0. Distribution: 80% in 0–5% bucket; 10% in 5–10% bucket; 10% in 10–20% bucket.
% Customers Earning <\$5/day (1.0)	5	0–10% (0.05); 10–30% (0.10); 30–50% (0.30); 50–80% (0.25); 51–60% (0.25)	If Average Monthly Income < \$200, available options are 30–50% and 50–80% only. If Average Monthly Income > \$500, excludes 30–50% and 50–80% options.

Notes: This table describes the components of synthetic company profiles used in the survey experiment. Column 1 lists each variable with its inclusion probability in parentheses. Column 2 reports the number of possible options for each variable. Column 3 lists the available options with their respective sampling probabilities. Column 4 describes any restrictions or conditional dependencies between variables. All monetary values are displayed in both USD and INR (Indian Rupees) in the profiles. Probabilities may not sum to exactly 1 due to rounding or conditional restrictions.

TABLE A6. Variable Definitions for Regression Analysis

Variable	Definition
Social Impact Variables	
CS Above Median	Indicator equal to 1 if total customer surplus is above the median (conditional on CS being displayed), 0 otherwise.
CS Below Median	Indicator equal to 1 if total customer surplus is below the median (conditional on CS being displayed), 0 otherwise.
Surplus Displayed	Indicator equal to 1 if customer surplus information was displayed in the profile, 0 otherwise.
Impact Sentence Displayed	Indicator equal to 1 if a qualitative social impact statement was displayed in the profile, 0 otherwise.
Financial Performance	
Profitable Firm	Indicator equal to 1 if the company reported positive profits, 0 otherwise.
High Revenues	Indicator equal to 1 if annual revenues exceed $50,000, 0 otherwise.
High Capital Raised	Indicator equal to 1 if total capital raised exceeds $55,000, 0 otherwise.
Company Characteristics	
Young Firm	Indicator equal to 1 if the company was founded after 2020, 0 otherwise.
Large Firm	Indicator equal to 1 if the company has 10 or more employees, 0 otherwise.
High Nr. of Customers	Indicator equal to 1 if the number of customers is above the median, 0 otherwise.
No Investors	Indicator equal to 1 if the company has not yet received external investment, 0 otherwise.

Notes: All variables listed here are binary indicators derived from randomized profile attributes and correspond to the X_{jk} regressors included in the main estimation equation (Equation III.1). Median thresholds are calculated within the sample of generated profiles. See Section D.1 for details on profile construction and randomization.

TABLE A7. Investment interest and company characteristics

	Investment Interest			
	(1)	(2)	(3)	(4)
Log Total Customer Surplus	0.107***	0.115***		
	(7.40)	(9.39)		
Log Average Customer Surplus			0.170***	0.206***
			(3.75)	(4.87)
Log Customer Income			0.072	0.097
			(0.64)	(0.97)
High nr. customers [0/1=Yes]	-0.003	0.011	0.353**	0.437***
	(-0.03)	(0.11)	(2.36)	(3.32)
Young Firm [0/1=Yes]	-0.105	-0.002	-0.037	0.189
	(-1.02)	(-0.02)	(-0.24)	(1.37)
Profitable Firm [0/1=Yes]	0.432***	0.421***	0.164	0.147
	(3.37)	(3.68)	(0.92)	(0.89)
Large Firm [0/1=Yes]	0.002	-0.007	-0.251	-0.132
	(0.01)	(-0.07)	(-1.50)	(-0.90)
High Revenues [0/1=Yes]	0.275***	0.175*	0.329**	0.389***
	(2.68)	(1.95)	(2.17)	(2.88)
High Capital Raised [0/1=Yes]	-0.054	-0.061	-0.213	-0.036
	(-0.49)	(-0.62)	(-1.34)	(-0.25)
No Investors [0/1=Yes]	-0.171	-0.086	-0.113	0.021
	(-1.47)	(-0.82)	(-0.69)	(0.13)
For-profit Company [0/1=Yes]	0.045	0.078	0.242	0.186
	(0.36)	(0.70)	(1.24)	(1.11)
Observations	1,338	1,338	696	696
Mean	4.43	4.43	4.36	4.36
Unique Investors	223	223	116	116
Respondent FEs	No	Yes	No	Yes
Profile FEs	No	No	No	No
R^2	0.072	0.498	0.052	0.477
Adjusted R^2	0.065	0.394	0.039	0.362

Notes: This table reports the coefficients of OLS regressions estimating the effect of firm variables on investment interest. The variable *Log Total Customer Surplus* represents the total customer surplus in USD (logged), while *Log Average Customer Surplus* and *Log Customer Income* denote the logged values of average customer surplus and customer income, respectively. *Investment Interest* is measured on a scale of 1–7. T-statistics, reported in parentheses, are based on robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. In columns (3) and (4), the sample is restricted to respondents who were part of the randomized group that received the additional surplus measure.

B. Additional Figures

FIGURE B1. Example Impact Report

IMPACT REPORT

Villgro IMMpact Program

Co-developed by professors from Chicago Booth & Harvard Business School, the Villgro IMMpact program aims to help start-ups and social enterprises implement effective Impact Measurement and Management (IMM) practices.

40

About Villgro

Villgro's mission is to make innovative, impactful social enterprises succeed.

Villgro helps social enterprises achieve sustainable impact at scale and philanthropic foundations achieve their sustainability & impact goals.

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Program Summary

The **Villgro IMMpact program** is the first of its kind, large scale causal examination of impact management and measurement practices (IMM) in Low Income countries supported by London School of Economics' international Growth Centre (IGC).

The aim is to identify best practices in impact management and to build the capacity of participating firms to measure and monitor their impact. To that end, we have conducted multiple training sessions with industry experts and mentors for impact measurement and monitoring. We have also engaged in rigorous 1-1 sessions for each firm to build their impact framework.

To provide our firms with a strong starting point in their impact journeys, we have conducted an all-expenses paid impact survey to understand the value they are creating for stakeholders. This report is a result of this survey and describes the impact an organisation has on its numerous stakeholders such as customers, employees and even suppliers. This is done on behalf of the firms by Institute for Financial Management and Research (IFMR) in collaboration with Villgro.

Program Methodology

Over 200 participating firms in the program that have been given an opportunity to attend monthly virtual training sessions with industry experts on best IMM practices.

The group then was approached for a data collection process in which impact data is collected by our team on their behalf, by surveying several customers, suppliers and employees of each firm.

As part of this process, each firm was also assigned a portfolio associate to help with the data collection process and with providing the firm with data and reports from the impact data being collected.

The training sessions were extended to practical multi 1-1 sessions with each firm to help them build an impact framework, so that firms can implement the lessons from the training sessions.

KEY DEMOGRAPHICS



CUSTOMERS



EMPLOYEES



SUPPLIERS



Customer Impact

We attempted to contact

528 customers

We were able to survey

86 customers

We estimate the average impact that your firm has on your customers to be

Rs. 351

per customer

To compute the impact that your company has on its customers, we collected the following data.

1

First is **how much they paid in their last transactions** with your firm. Among respondents, this was

Rs. 5,151

on average[1]

2

We then asked customers to tell us their **reservation value** for this transaction – the largest amount they would be willing to pay to purchase that same set of goods or services, accounting for all similar goods or services available in their market. On average, customers reported this to be

Rs.5,501

1 Note that if a customer received a product for free, the price that they paid is taken to be Rs.0.

CONSUMER SURPLUS

The firm's impact is computed as the difference between these two numbers: the amount they paid in their last transaction less their reservation value. This notion of customer impact corresponds to the economic notion of "consumer surplus."

Why is consumer surplus a natural measure of impact on your customers?

A firm's impact on its customers can be highly multifaceted. For instance, a firm that provides organic food might impact customers' health and their enjoyment of their meals. Customers might also value the fact that the products are responsibly sourced. They may derive a host of other benefits as well, such as how pleasant it is to shop at the store or the quality of the firm's customer service. So long as a customer understands all of these benefits, when they report their reservation value – the most they would be willing to pay for this product – they are accounting for all of the various benefits they derive from the firm's goods or services and determining on their total value.

The difference between the total value they enjoy and what they pay for the product is the excess value, or customer impact delivered in that transaction.

The average customer reported a household income of Rs.107,881 per month.. After accounting for their household income, this would be equivalent to increasing their household income by 1.0% each time one of your customers avails your firm's goods or services.[2]

To estimate the total impact that your firm has on its customers every month, you can multiply the number of transactions your firm has per month by the average impact reported above. For example, we received contact information for 528 customers and the average customer reported having 0.5 transactions per month. Scaled across your firm, this value is equivalent to generating Rs. 92,615 worth of impact on your customers every month (Average Surplus x Number of Customers x Number of Transactions per Month).

2 To compute this number, we divide the surplus computed for each customer and divide it by their household income (for those that reported their household income). We then take the average of this fraction across all customers.

In Figure 1a, we plot the last amount paid by each of the 86 customers and how much they would have been willing to pay for that transaction. The difference between these two bars is the customer surplus (we plot this difference in Figure 1b). Note that the customer surplus can be negative if a customer would not have been willing to pay the same price they paid in the last transaction.

Fig.1a Customer Willingness to Pay

Last Amount Paid
Maximum Willing to Pay

Number of responses- **86**
Average last amount paid- **5,151 INR**
Average willingness to pay- **5,501 INR**

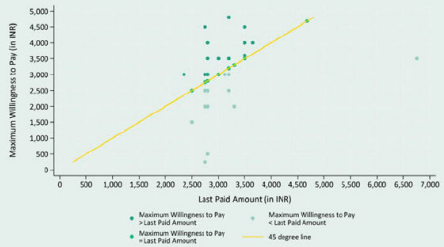
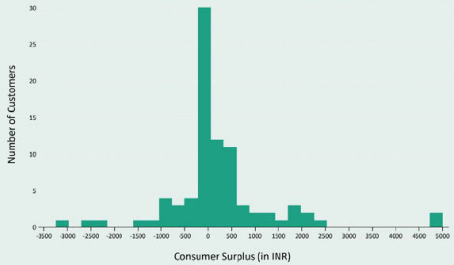


Fig.1b Customer Surplus

Customer surplus = Willingness To Pay - Last Paid

Number of responses- **86**
Average consumer surplus- **Rs. 351**



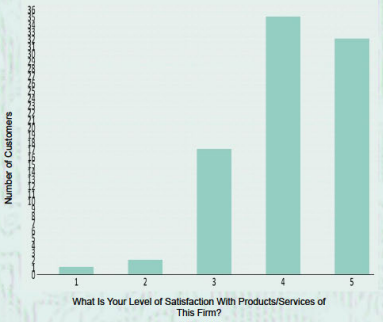
CUSTOMER SATISFACTION & RECOMMENDATION

We collected information on how satisfied your customers felt about your products and services (on a scale of 1-5) and also how likely they are to recommend your firm to their friends and family (on a scale of 1-5).

In Figure 2, we plotted a distribution of customer satisfaction. On average, customers reported **4.1** on the satisfaction scale.

Fig.2 What Is Your Level of Satisfaction With Products/Services of This Firm?

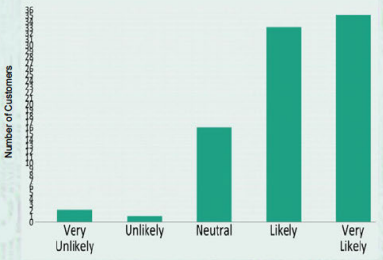
Number of responses- **86**
Average level of satisfaction- **4.1**



In Figure 3, we plotted a distribution of customer recommendation. On average, customers reported **4.1** on the recommendation scale.

Fig.3 How Likely Are You To Recommend This Firm to Friends and Family?

Number of responses-**86**
Average level of recommendation- **4.1**



Employee Impact

We attempted to contact
3 employees

We were able to survey
3 employees

Of the 3 employees who responded, 1 were current employees. Unless otherwise specified, the data presented in this report will include all current and former employees who responded to the survey.

We estimate the average impact that your company has on its employees to be
Rs. 2,334
per employee.

To compute the impact that your company has on its employees, we collected the following data.

1

First is their current **monthly salary.** Among respondents, the average monthly salary was

Rs. 16,667

2

We then asked employees to tell us their **reservation salary**– the smallest monthly salary they would be willing to accept to continue working at your firm, accounting for all of their other employment options. On average, employees reported this to be

Rs. 14,333

EMPLOYEE SURPLUS

The firm's impact is computed as the difference between these two numbers: employees' current salary less their reservation salary. This notion of employee impact corresponds to the economic notion of "employee surplus."

Why is employee surplus a natural measure of impact on your employees?

Employee surplus is similar to consumer surplus but applied to the context of employment. It represents the extra value or benefit that employees receive from their jobs beyond what they have to sacrifice, such as their time and effort.

Just as a customer's value of your goods or services is multifaceted, employees may derive many types of benefits from working at your firm, beyond their salary. These may include the quality of the work, the culture and mission of the organization, and other non-monetary amenities. An employee's reservation salary captures how much money they would require to work at the firm, taking into account all of the relevant considerations including what they could earn elsewhere, and the various non-monetary benefits they enjoy at your firm. The difference between what you pay them and their reservation salary is then the value, or impact, that you deliver to them in excess of what they would require to continue doing the work.

In essence, employee surplus measures the satisfaction and overall benefit that employees derive from their work, considering factors like wages, job perks, and other non-monetary rewards.

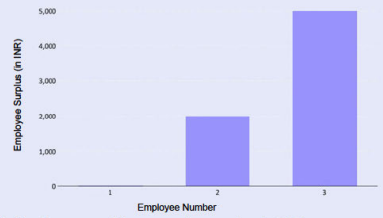
For the average employee who responded to the survey, employee surplus amounts to **12.2%** of their monthly salary. Thus far, we have reported surplus of all employees who responded to the survey. If, instead, we limited the analysis to current employees who responded to the survey, their average employee surplus is 5,000. This amounts to 16.7% of their current monthly salary.

In Figure 1, we plot the surplus reported by each of the 3 employees so that you can observe how the surplus varies across respondents. Note that unlike in the customer surplus report in which we show the price paid and the surplus, we do not plot salary and surplus together. We do not display these data because of confidentiality concerns – displaying the salary of individual employees, particularly in a small sample, could make a employee identifiable and therefore violate the confidentiality of their individual responses.

To estimate the total impact that your firm has on its employees, you can multiply the number of employees your firm currently has by the average impact reported above. Your firm provided contact information for 3 employees (excluding founders and upper management). Scaled across your firm, this value is equivalent to generating Rs. 7,001 worth of impact on your employees every month.

Fig.1 Employee Surplus

Employee surplus = current salary - minimum salary willing to accept



Number of responses- **3** | Average employee surplus- **Rs.2,334**

EMPLOYEE SATISFACTION & RECOMMENDATION

We collected information on how satisfied your employees felt about their jobs (on a scale of 1-10, with higher numbers indicating higher satisfaction) and also how likely they are to recommend working at your firm to their friends and family (on a scale of 1-5, with higher numbers indicating higher recommendation).

In Figure 2, we plotted a distribution of employee satisfaction. On average, employees reported **9.3** on the satisfaction scale.

Fig.2 What Is Your Level of Satisfaction With Your Job?

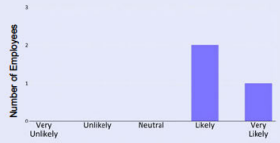
Number of responses- **3**
Average level of satisfaction- **9.3**



In Figure 3, we plotted a distribution of employee recommendation. On average, employees reported **4.3** on the recommendation scale.

Fig.3 How Likely Are You To Recommend Working At The Firm to Friends and Family?

Number of responses- **3**
Average level of recommendation- **4.3**



Supplier Impact

We attempted to contact

5 suppliers

We were able to survey

1 suppliers

To get a fully representative picture of the impact your company has on your suppliers, it is important to reach a larger fraction of them. Nevertheless, the following statistics provide an indication of your company's impact.

We estimate the average impact that your company has on its suppliers to be

Rs. 0

per supplier

To compute the impact that your company has on its suppliers, we collected the following data.

1

We asked the revenues they earned from the last sale they made to your company. Among respondents, the **average revenue** was

Rs. 30,000

2

We then asked suppliers to tell us their **reservation value** -- the smallest amount they would be willing to accept to make that same last sale. On average, suppliers reported this to be

Rs. 30,000

SUPPLIER SURPLUS

The firm's impact is computed as the difference between these two numbers: suppliers' revenue from their sale to your organization less their reservation value. This notion of supplier impact corresponds to the economic notion of "supplier surplus."

Why is supplier surplus a natural measure of impact on your customers?

Supplier surplus is similar to consumer surplus but applied to the context of sales to (rather than purchases from) your organization. It represents the extra value or benefit that suppliers receive beyond what they have to sacrifice, such as their effort and resources.

Just as a customer's value of your goods or services is multifaceted, suppliers may derive many types of benefits from working with your firm, beyond their sales. These may include the quality of the work, the culture and mission of the organization, and other non-monetary amenities. A supplier's reservation value captures how much money they would require sell goods to your firm, taking into account all of the relevant considerations including what they could earn elsewhere, and the various non-monetary benefits they enjoy from your firm. The difference between what you pay them and their reservation value is then the value, or impact, that you deliver to them in excess of what they would require to continue doing the work.

SUPPLIER SATISFACTION & RECOMMENDATION

We collected information on how satisfied your suppliers felt about your firm (on a scale of 1-10, with higher numbers indicating higher satisfaction) and also how likely they are to recommend working with your company to their friends and family (on a scale of 1-5, with higher numbers indicating higher recommendation).

On average, suppliers reported **9** on the satisfaction scale and **5** on the recommendation scale.

SUMMARY OF CUSTOMER RESPONSES

1. How would you rate the value for money of (product/service) of [redacted]? Scale of 1 to 10 [10 being positive]. Please explain your rating.

The average rating given to [redacted] by 86 respondents is 8.

A substantial 26% (22 customers) rated it a perfect 10, while 14% (12) rated it a 9, lauding its quality and performance.They highlighted its '*durability*', '*reusability*', and *'fuel efficiency improvements'*. Many described it as a '*one-time investment*' with benefits like '*increased mileage*' and '*smooth throttle response*', comparing its quality to international brands while noting its affordability. Users appreciated that it served its purpose well, with some noting it as a '*valuable*', '*eco-friendly*', and *'long-lasting product'*.

Another 44% (37 customers) rated it between 6 and 8, expressing moderate satisfaction with the product performance. Some of them expressed concerns with the '*high pricing*' and some mentioned that there is '*scope of improvement in fuel efficiency and overall performance'*.

In contrast, 16% (14 customers) rated the product 5 or below, highlighting issues like '*poor material quality'* and '*failure to deliver on advertised performance gains'*. They were particularly dissatisfied with the high price point, feeling it did not match the product's actual performance outcomes.

Overall, customer feedback highlights a mixed reception towards the product's value proposition, with emphasis on balancing cost-effectiveness and tangible performance benefits to meet diverse customer expectations effectively.

SUMMARY OF CUSTOMER RESPONSES

2. Why do you choose to purchase the products/services of [redacted] over others?

A. Pricing
B. Quality
C. Customer Service
D. Trust in the Company/ Founders
E. Sustainability

Of the 86 customers who responded to this question, 60 selected **'Quality'**, 40 selected **'Pricing'**, 35 selected **'Sustainability'**, 31 selected **'Trust in the Company/ Founders'** and 22 selected **'Customer service'**, as reasons to purchase Small Sparks products over other alternatives.

Many respondents selected multiple options to answer this question.

3.Describe how you feel about your experiences with customer service at [redacted]?

Customers had varied experiences with the customer service at [redacted]

Majority of respondents (around 54%) reported having a positive experience with the customer service. They described their experiences as 'good', 'very good', 'excellent', or 'great'. They appreciated timely responses, helpful interactions, and support via social media channels like WhatsApp and Instagram.

Nearly 41% of the respondents either had a satisfactory experience or no experience at all with the customer service. Many said that they didn't feel the need to reach out to the customer service yet, while others had no complaints.

A very small fraction of the respondents (4, 5%), shared that there aren't happy with the customer service and said it needs to be improved.

SUMMARY OF EMPLOYEE RESPONSES

1. What are additional products, features or services that you wished [redacted] provided that it does not currently?

Of the 3 respondents to this question, 1 said that the products can be more refined and the delivery can be made quicker. Another said [redacted] can be some additional products/ features. While 1 respondent said that there are no additional products, features or services that they wished [redacted] provided that it does not currently.

2.What can [redacted] do to improve its existing product/ service being offered currently?

When the employees were asked what can [redacted] do to improve its existing product/ service being offered, of the 3 respondents, 2 said that the firm can 'increase its capacity and invest more on quality control of product', while 1 said that the firm should 'increase its reach to potential customers and businesses'.

An employee additionally shared that [redacted] is a great company to work with where ideas are valued, learning from the founders is encouraged, and employee satisfaction and comfort are prioritized.

3.List out possible new target customers, geographies you think the company could target?

When responding to suggestions on new target customers and geographies, of the 3 respondents 1 said that the firm should target '*tropical countries'* while the other said that possible targets could be *'anywhere in the world where the air is polluted more than normal operating conditions for a vehicle'*.

1 respondent said that the firm should target '*regular transport vehicle agencies, Rider groups and Service Centres'* as their new customers.

SUMMARY OF
SUPPLIER RESPONSES

1. Rate your experience on receiving payments from [redacted]
Scale 1-10 [10 being positive].

The respondent to this question rated their experience on receiving payments from [redacted] as a perfect 10. They said that the firm always makes timely online payments.

2. Rate your experience with the purchase team of [redacted].
Scale 1-10 [10 being positive].

The respondent to this question rated their experience with the purchase team of [redacted] as a perfect 10.

They said that they have had a very good experience with the product team of [redacted]. They also appreciated the product saying that it is 25% more sustainable than the other products in market. They are happy to have good supplier relations with the firm.

3.Do you find the information and updates provided by [redacted] team clear and easy to understand?
Scale 1-10 [10 being positive].

The respondent to this question rated a perfect 10 saying that they are able to understand all updates from the firm and their doubts are also cleared by the firm when needed.

Appendix

The process of administering surveys for this report involved a multi-faceted approach utilizing both WhatsApp and phone calls. Initially, respondents were provided with personalized links to access and complete the survey in either Hindi or English through the WhatsApp platform. This method allowed for convenient and accessible participation, accommodating respondents' language preferences. In instances where respondents did not engage with the survey via WhatsApp within a 2-4 day period, a dedicated team of surveyors embarked on a follow-up phase. This phase involved making direct phone calls to individuals who had not yet participated in the survey through the WhatsApp links. The objective was to ensure maximum participation and representation across the target demographic.

Surveyors diligently attempted to conduct the survey over the phone, offering flexibility to respondents who might prefer verbal communication or encounter technical difficulties with online participation. Each phone number received persistent outreach efforts, with surveyors making 4-5 attempts to establish contact and facilitate survey completion.

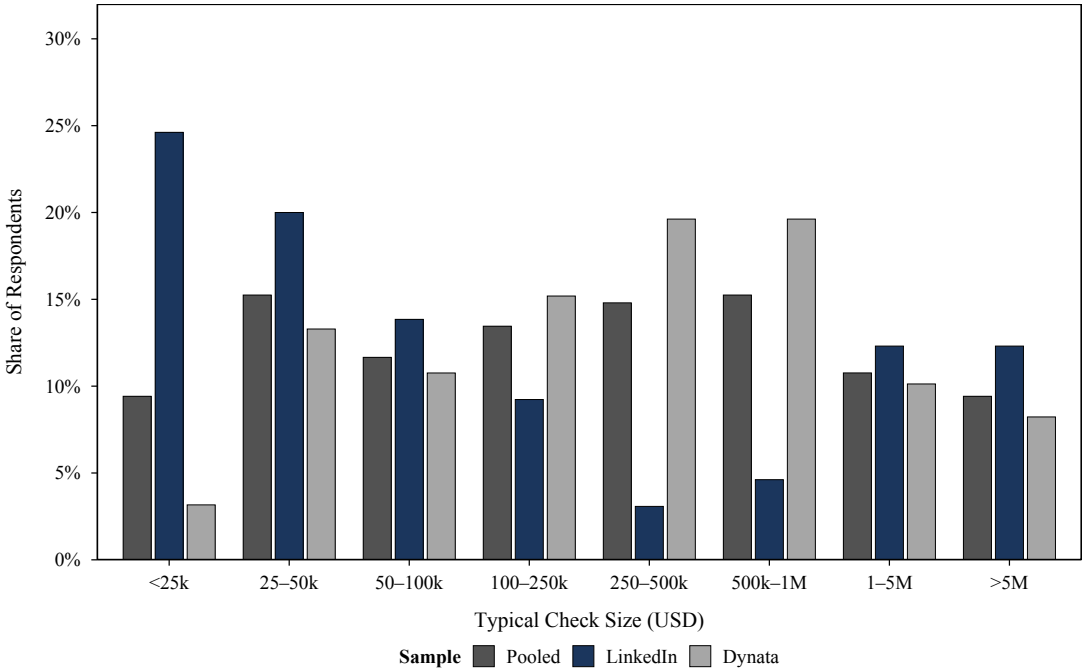
This comprehensive methodology aimed to minimize barriers to participation, ensure inclusivity, and gather diverse insights from the surveyed population.

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FIGURE B2. Distribution of Typical Check Sizes by Recruitment Channel



Notes: This figure displays the distribution of typical check sizes across the pooled sample (N=223) and by recruitment channel: LinkedIn networks (N=65) and Dynata (N=158).