

AN APPLICATION OF STATISTICAL MODELS TO ENERGY AND LABOR MARKETS

by

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ABSTRACT

The thesis explores empirical questions in energy and labor economics. In the first chapter, econometric techniques are employed to investigate the relationship between household access to electricity, hours of supply of electricity, and labor market outcomes, specifically, labor participation rates and number of working hours. Our results indicate limited effects of electricity reliability on rural and slum populations. For urban populations, electricity reliability improves both labor participation rates and labor hours for men and total populations, however, the magnitudes of these effects are small. Further, our results also suggest that men benefit more than women from reliable electrification with improved labor market outcomes in urban contexts, however, this does not hold true for rural contexts.

In the second chapter, we ask what creates effective reciprocity in online labor markets. We investigate the gift exchange hypothesis using a large field experiment conducted through a crowdsourcing platform. We find that gift exchange or bonuses incentivize workers to spend more time on tasks and induce them to complete more tasks. However, they do not necessarily improve all dimensions of the data quality or outcome of a complex task. We also learn that outcomes can be improved on some dimensions i.e., completeness and productivity by skill matching.

In the third chapter, we examine the relationship between distribution grid reliability and distributed solar capacity using proprietary utility feeder level data on reliability and solar installed capacity and econometric methods. Our results indicate that presence of solar capacity on a feeder, can help reduce outage duration on the feeder, while it does not impact the frequency of the outages. This relationship is dependent on the number of customers on the feeder. Low population feeders see improvements in reliability, with installation of solar capacity.

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For my Father...

CHAPTER 1

INTRODUCTION

The thesis consists of three essays that explore different questions in energy and labor economics. The chapter provides a brief summary and major contribution of each chapter.

Chapter 2 evaluates the impacts of reliable electrification on labor market outcomes of populations across India. Access to household electricity is important to end poverty, however, access alone does not provide a complete picture. For households which are grid connected, the supply is often unreliable with frequent outages. Existing literature on the role of electricity in economic development, extensively explores the impact of access to electricity on household outcomes while not sufficiently explaining how additional hours of electricity can affect economic outcomes. We fill this gap in literature by exploring the relationship between electricity reliability and labor market outcomes across households in India, by gender and region i.e., across rural, urban and urban slum households. The only other study to look at reliability impacts along these dimensions finds very different results from ours and we see our work as complementary to this existing work by Sedai et al., 2021. In their research, to address endogeneity in electrification access and reliability they use an identifying strategy which depends on variation of electricity reliability mean at the state level, whereas in our research, we use electricity reliability means at the village level. This difference in variation in the research design, helps us explore important heterogeneous electrification treatment effects which have not been previously discussed in literature.

In Chapter 3 we explore what creates effective reciprocity in online labor exchange. We answer the question using the gift exchange hypothesis, according to which, employers may pay more than the market rate for labor services in order to reinforce norms in which workers provide more than the minimum effort and high-quality work above the minimum contractual (Akerlof, 1982). Most previous literature which tests the gift exchange hypothesis does this in a context where the contract is complete. Our novel contribution to this growing field is to study the online labor market and to test the gift exchange

hypothesis in a context where the contract is truly incomplete. Existing literature assess workers on data quality of unambiguous data entry tasks, whereas, in our study we use both ambiguous and unambiguous task components which makes our study results and contributions novel.

In chapter 4, we evaluate the distribution grid reliability impacts of distributed solar and contribute to the literature which studies the impacts of distributed solar capacity on the distribution grid. Previous literature on the topic, particularly evaluating the reliability impacts of the distributed solar, is scarce. Further, existing literature typically relies on simulated data of a single feeder or feeder type or climate, which makes the results of these studies less generalizable. In our research, we use a unique panel dataset of feeder level reliability and solar installations, which captures varying climates, loads supplied and feeder topology. Therefore, our research estimates capture the true complexity of the grid topology and the socio-economic context associated with it. Additionally, our research provides methods and estimates of this impact using actual feeder data, which can be potentially used to calculate reliability and resiliency costs and benefits of distributed solar capacity for the distribution grid.

1.1 Summary of Chapter 2

In this paper we explore the relationship between household access to electricity, hours of supply of electricity, and labor market outcomes, specifically, labor participation rates and number of working hours. We study the variation of labor market outcomes for men and women in rural, urban, and slum populations as an effect of household access to reliable electricity. Employing the two stage least squares (2SLS) method, this analysis uses two instrumental variables i.e., mean access rates and mean number of hours of electric supply at the village level. Our results indicate limited effects of electricity reliability on rural and slum populations. We see that as reliability of electricity increases, there are no improvements in rural and slum populations. For urban populations, electricity reliability improves both labor participation rates and labor hours for men and

total populations, however, the magnitudes of these effects are small. Our results imply that improved reliability has more positive effects on urban populations as compared to rural populations. Further, our results also suggest that men benefit more than women from reliable electrification with improved labor market outcomes in urban contexts, however, this does not hold true for rural contexts.

1.2 Summary of Chapter 3

In this study, we ask what creates effective reciprocity in online labor markets. A long literature has characterized employment relationships as “gift exchange”: employers provide fair treatment above the minimum legal requirement and employees reciprocate with high quality work above the minimum contractual requirement (Akerlof, 1982, Kube, Marechal, & Puppe, 2012). We investigate the gift exchange hypothesis using a large field experiment conducted through MTurk. Workers were hired to enter data about renewable energy investments from corporate sustainability reports. The reports did not have standard formatting, so judgment and effort were required in order for workers to provide quality data. Experimental treatments varied the wage rate, payment assurances, and task descriptions, in order to induce variation in both total compensation and worker expectations before beginning the task. We then measure worker effort and productivity or speed along with three key dimensions of data quality: data completeness, accuracy, and validity.

We find that gift exchange or bonuses incentivize workers to spend more time on tasks and induce them to complete more tasks. However, they do not necessarily improve all dimensions of the data quality or outcome of a complex task. We also learn that outcomes can be improved on some dimensions i.e., completeness and productivity by skill matching.

1.3 Summary of Chapter 4

The distributed solar capacity in the U.S. is forecasted to triple over the next decade. This makes it critical to understand the impacts of installed solar capacity on the distribution grid. Our research investigates the relationship between distribution grid

reliability and distributed solar capacity. We use a proprietary utility panel dataset with reliability metrics and installed solar capacity at the feeder level for 8 years and merge it with demographic and weather datasets to answer our research question. We estimate the effect of distributed solar capacity on distribution grid reliability metrics. To address endogeneity, we use a shift share instrument – which is an interaction of solar irradiance at the feeder location and the cost of solar modules over the 8-year timeframe. Our results indicate that presence of solar capacity on a feeder, can help reduce outage duration on the feeder, while it does not impact the frequency of the outages. This relationship is dependent on the number of customers on the feeder. Low population feeders see improvements in reliability, with installation of solar capacity.

CHAPTER 2
IMPACTS OF ACCESS TO RELIABLE ELECTRICITY ON LABOR MARKET OUTCOMES
IN INDIA

2.1 Introduction

Access to electricity is a key driver of economic and social development. Providing access to reliable electricity is critical for reaching sustainable developmental goals in underdeveloped and developing countries around the world. Research shows positive benefits of access to electricity on household income, education of children and employment (Akpanjar and Kitchens, 2011; Allcott, Collard-Wexler, O'connell, 2016; Chakravorty, Pelli, and Marchand, 2014; Dinkelman, 2011; Grogan and Sadanand, 2013; Khandker, Barnes, and Samad, 2012; Khandker, Samad, Ali, and Barnes, 2012; Lipscomb, Mobarak, and Barham, 2013; Van de Walle, Ravallion, Mendiratta, and Koolwal, 2013). However, millions still lack access to reliable electricity in developing countries around the world.

Even when households are connected to the electric grid, they may have an unreliable supply. This may result in power outages for grid connected households. These outages may vary in frequency and duration. Outages can be caused by technical problems faced by the electric grid such as equipment failure which can last long hours. On the other hand, several utilities face power shortages which can lead to more predictable load shedding, which is often experienced in developing countries and can last a few hours in the day. In India, utilities regularly fail to meet the electricity demand due to insufficient power generation which leads to rolling blackouts around the country (Allcott et al., 2016). This cycle leads to an unreliable supply of electricity even in countries with high access rates, i.e. countries where a large percentage of the population is connected to the electric grid (Gertler, Lee, Mobarak, and Mushfiq, 2017).

The World Bank Doing Business (WBDB) project reports two measures of electricity reliability, System Average Interruption Duration index (SAIDI) and System Average Interruption Frequency Index (SAIFI). SAIDI annually measures the duration of power

outages while SAIFI annually measures the frequency of power outages experienced by a customer. Using data from 179 countries, Ayaburi, Bazilian, Kincer, and Moss, 2020 found that globally, 789 million people lack access to electricity, while 3.45 billion did not have reliable electricity with greater than 12 hours of power supply in a day. In the same vein, (Gertler et al., 2017) reported that high income countries had low SAIDI and SAIFI rates, while developing countries were often distinguished by low access rate and high SAIDI and SAIFI rates. Similarly, using another dataset, comparing access and reliability rates in Sub-Saharan African (SSA) cities, they report that reliability rates were considerably lower even as access rates were increasing.

Access to electricity or bringing grid electricity to new households is important to end poverty. However, access to electricity alone does not provide a complete picture, providing high quality reliable electricity with fewer outages can have a significant impact on macroeconomic, household and firm economic outcomes. Without reliable supply of electricity, the full potential of electrification benefits particularly in economic, social and educational outcomes may not be fully reached (Allcott, Collard-Wexler and O'connell, 2016; Chakravorty et al., 2014). Anderson and Dalgaard (2013) found that between 1995 and 1997, a one percent increase in power shortages reduced the long run GDP per capita by 2.86 percent. At the household level, research has found that income can significantly increase for households with reliable electricity (Chakravorty et al., 2014; Rao, 2013).

Besides economic outcomes, research has shown that outages can also have considerable impact on health outcomes (Burlando, 2014). Allcott, Collard-Wexler and O'connell, 2016 show that power outages across manufacturing firms in India can lead to a reduction in average revenues of plants by 5 to 10 percent, however small productivity losses were observed.

Affordability, availability, and reliability varies widely amongst households which are connected to the grid. Electricity access and reliability are critical issues for rural and urban households, however traditionally low electricity access rates in rural areas, has led to research focus on expansion of rural electrification programs, which may not be focused

on reliability of the electric connection. On the other hand, while urban households are often connected to the grid, reliability of the electric grid remains a key concern in urban areas (Gertler et.al, 2017). Gertler et.al, 2017 argue that reliability of electricity is more critical in urban areas due to overcrowding and electricity theft in cities, and due to higher opportunity costs of outages in cities. Electricity reliability issue in cities are exacerbated by intra urban differences caused by presence of urban slums (Aklin, Bayer, Harish, and Urpelainen, 2014). More than half the global population in the world currently lives in cities, and this number is expected to double by 2050. With growing urban populations, it becomes critical to improve energy access and reliability of electricity in cities in addition to rural populations. This makes it important to understand how access to electricity and reliability effect economic outcomes in rural, urban and slum populations.

This research focuses on labor market outcomes in urban, rural and slum households in India. The main aim of this research study is to establish the relationship between access to reliable electricity in households and labor market outcomes. More specifically, this research seeks to address the following questions:

1. What is the relationship between labor supply and household electricity access and reliability?

- 1.1. What are the heterogeneities we can observe across regions i.e., rural, urban and urban slum areas?

- 1.2. What are the heterogeneities we can observe across gender?

The methodological approach taken in this study to identify the relationship between labor market outcomes and access to reliable electricity is econometric. Provision of access to electricity is not randomized for communities or households. Therefore, it could be endogenous to labor market outcomes. A simple regression in such a case would give biased estimates. An empirical identification strategy based on use of instrumental variables is used in this paper to deal with the existing endogeneity. Following literature, the instrument used to identify household electricity access and reliability is mean level of household electricity access in a community and mean level of number of hours of

electricity supplied to households in a community (Khandker et al., 2012; Rao, 2013). These instruments directly impact the household demand for electricity through peer effects, however they do not impact the household labor decisions. The research data used in this paper is drawn from a nationally representative survey of over 41,554 households. Mean level of access to electricity of households in a community and mean level of number of hours of electricity supplied to households in a community, excluding the household itself, are a potential instrument for all sources of bias.

This paper contributes to the literature demonstrating the use of applied micro econometric techniques in questions of household electrification and employment in the following aspects. Firstly, this research will contribute towards a large and growing body of literature which investigates the role of electricity in economic development (Akpanjar and Kitchens, 2011; Allcott et al., 2016; Burlig and Preonas, 2016.; Chakravorty et al., 2014; Dasso and Fernandez, 2011; Dinkelman, 2011; Aklin et al., 2014; Grogan and Sadanand, 2013.; Lipscomb et al., 2013; Pueyo and Maestre, 2019; Rao, 2013; Salmon and Tanguy, 2013.; Rathi and Vermaak, 2018; Sedai, Vasudevan, Pena, and Miller, 2021; Van de Walle et al., 2013). Within the Indian context, research exploring benefits of electrification has primarily been focused on access of households to electricity (Chindarkar, Chen, and Sathe, 2020; Khandker, Samad, et al., 2012; Samad and Zhang, 2016.; Rathi and Vermaak, 2018; van de Walle et al., 2013). This body of research studies the impact of electricity access on household incomes, consumption, employment, education and health outcomes. Very few studies investigate the impacts of reliability of the electric supply on household outcomes (Ahmad, Mathai, and Parayil, 2014; Chakravorty et al., 2014; Rao, 2013, Sedai et al., 2021). Allcott, Collard-Wexler and O'Connell, 2016 explores the impact of outages on manufacturing firms and Chakravorty et al., 2014 and Rao, 2013 studies the impact of reliability on household incomes. Ahmad et al., 2014 examines the impact of electricity accessibility and availability on human welfare, particularly education and health outcomes. Secondly, while impacts of access to electricity on rural households and communities are well captured in the literature, limited attention

has been paid to impacts of electricity access and reliability on urban and urban slum populations (Ahmad et al., 2014; Aklin et al., 2014).

This study begins to address the gap in literature and investigates how access to a reliable electric supply can affect labor market outcomes in rural, urban and slum populations. The only study that investigates the causal effects of reliable electricity on labor and non-labor market outcomes for men and women is Sedai et al., 2021, and we see our work as complementary to this existing work. They examine the electricity supply reliability in rural and urban areas using IHDS data from two waves and the Access to Clean Cooking Energy and Electricity Survey (ACCESS, 2015–2018). They use a panel fixed effects and instrumental variable regression model in their analysis. They use the average hours of household electricity at the state level, excluding one’s own district as an instrument in their analysis. They find that improving electricity reliability of a household increases the labor participation rates of men and women, while reducing labor work hours for men, and not women; and this effect is larger for women as compared to men in both urban and rural areas in India.

Our results, have some striking differences from their work. First, we observe that increased access to reliable electricity, does not show an improvement in labor market outcomes in men, women and total populations in rural and slum areas. Second, while we show a positive effect of supply reliability in urban areas on labor market outcomes, the magnitudes are much lower as compared to those found by Sedai et al., 2021. Looking at a gendered analysis of these populations, we see that men benefit more than women with reliable electrification in urban areas, whereas this effect is less prominent in rural areas. More specifically, increasing access to electricity can reduce labor participation rates worked for rural men, while having no significant impact on rural women and total rural populations. On the other hand, urban men and total urban populations see more positive impacts of electricity reliability on labor market outcomes as compared to urban women, however these impacts are small in magnitude.

The rest of this paper is divided into five parts. Section 2 reviews the literature and

theoretical models. Section 3 summarizes the background of electrification in India and the labor markets in India. Section 4 addresses the methodology, including the data and the empirical strategy, Section 5 discusses the results, section 6 is the discussions and section 7 presents the research conclusions.

2.2 Literature Review

Several attempts have been made to examine the effects of energy access on social, health and economic outcomes. A considerable amount of literature has employed use of empirical techniques to understand the causal mechanisms which link access to electricity and economic outcomes of employment (Akpanjar and Kitchens, 2011; Allcott, Collard-Wexler and O'Connell, 2016; Chakravorty et al., 2014; Dinkelman, 2011; Grogan and Sadanand, 2013; Khandker, Barnes et al., 2012; Khandker, Samad et al., 2012; Lipscomb et al., 2013; van de Walle et al., 2013). Much of the early literature on electrification pays particular attention to energy access in rural areas and studies the benefits of rural electrification programs. This literature claims that rural access to electricity provides welfare growth of households (Barnes, Peskin, and Fitzgerald 2003; Martins 2005). However, Khandker, et al., 2012 argued that the early literature exploring the relationship between rural households access to electricity and development fails to develop causal links as they are unable to address endogeneity concerns of selection and program placement biases. More recent literature addresses these concerns and measures the effects of access to electricity on the economic outcomes such as employment (Akpanjar and Kitchens, 2011; Chakravorty et al., 2014; Dinkelman, 2011; Khandker et al., 2012; Salmon and Tanguy, 2016), firm productivity (Allcott, Collard-Wexler, and O'Connell, 2016) and household welfare (Khandker, et al., 2012; Van de Walle et al., 2013). In this section we focus on studies exploring the relationship between access to reliable electricity and labor market outcomes.

2.2.1 Impacts of access to electricity on employment

Several studies measuring the impact of access of electricity on economic outcomes in rural areas, particularly for women, predict an increase in labor participation rates of rural women as access to electricity is gained, due to freeing up of time previously spent on time-consuming domestic activities (Dinkelman, 2011; Grogan and Sadanand, 2013), however, the research on labor force participation and electrification has been inconclusive so far. Dinkelman, 2011 found that access to electricity led to an increase of almost 9.5 percent in labor participation rates of women in rural areas in South Africa, whereas she found no significant effects on labor participation rates of men in rural areas. Dinkelman (2011) studied these effects by creating a variation in electricity program placement through the use of a geographic instrument i.e., household land gradient. The author attributed the increase in female employment, to women substituting reduced time devoted to household activities such as collecting firewood, for income generating activities such as establishing microenterprises. Use of time saving appliances such as electric stoves encouraged such substitution. Similarly, in Nicaragua, Grogan, and Sadanand (2013) found the propensity of women to work in rural areas increase by 23 percent as a result of access to electricity, since women in rural households spend less time on household activities such as collecting firewood. Additionally, they used the extended light hours, to work longer and used the extra income from longer worked hours to buy firewood, instead of collecting it. They did not find any significant effects on participation rates of men. In the same vein, Dasso and Fernandez, 2011, using difference - in - difference and fixed effect approaches, concluded that access to electricity increased employment, hours worked and earnings amongst rural women in Peru.

Some studies have examined effects of rural access to electricity in India on employment outcomes. Van de Walle et al., 2013 detected an increase in labor supply of men and women as access to electricity in rural India increased. They found with increased access there was an increase in regular wage work for men and male employment moved

from irregular and casual work to the formal sector; and an increase in casual work for women. Similarly, Khandker et al., 2012 found positive effects of access to electricity on labor supply of men and women, with a greater impact on women.

Nevertheless, some recent efforts, have contradicting findings, and found many of the effects of electricity on economic and noneconomic outcomes to be statistically indistinguishable from zero. Rathi and Vermaak, 2018 examined labor markets in South Africa, and found little improvement in labor market outcomes of rural populations, both men and women with increased electricity access contrary to Dinkelman, 2011. Burlig and Preonas (2016) used regression discontinuity to study impacts of household electrification in India and found no evidence of economically or statistically significant impacts of electrification on labor market outcomes of men and women in rural areas. They found a shift in sectoral workers from agricultural to non-agricultural sectors, in the rural male employed population, however since the size of these shifts was small, they did not find change in total rural male labor allocations. Their results were consistent across poor, and non-poor households, communities with under and over 300 habitants, small and medium term, and across states with different reliability levels. Another, a randomized control trial in rural Kenya, showed no significant impacts of household access to electricity on economic and non-economic outcomes (Lee, Miguel, and Wolfram, 2020). The authors looked at the growth of the grid infrastructure and a program to bring electricity to 150 rural communities in Kenya. Within these communities, randomly selected clusters of households were provided the opportunity to connect to the grid at subsidized prices. They estimate the demand and cost curves for grid connection of households, and exploit the exogenous variation induced by the randomized subsidy offers to grid connected households, to estimate household electrification effects. In the same way, Lenz, Munyehirwe, Peters, and Sievert, 2017 used a panel dataset and difference-in-difference identification strategy to examine effects of Rwanda's electrification program on economic outcomes amongst other variables, and they found no significant effects on household income.

2.2.2 Impacts of electricity reliability on economic outcomes

Some studies on rural electrification in India include analysis of the reliable electricity supplied and its impacts on economic outcomes (Chakravorty et al., 2014; Aklin et al., 2014; Rao, 2013). Chakravorty et al., 2014 examines the effects of access to reliable electricity, on household income. They use the India Human Development Survey (IHDS) panel dataset for the years 1994 - 2005. They use an instrumental variable approach to deal with endogeneity and use district-level density of transmission cables as an instrument. They find that while access to electricity increased household non-agricultural incomes by 9 percent, reliable electricity with reduced outages increased non-agricultural incomes by over 28 percent. Rao (2013) used national cross sectional data and found evidence of increased non-farm income with improved reliability; such that improving supply to 16 hours of electricity a day for non-farm enterprises would amount to about 0.1 percent of India's GDP. Ahmad et al., 2014 explored the causal relationship between energy access and reliability and human welfare by employing linear regression analysis. They found a significant effect of electricity reliability on human welfare in rural and urban households, while accessibility had only a significant effect on human welfare of rural households in India. Sedai et al., 2021 examined the impacts of electricity reliability on labor market outcomes of male and female populations in India and concluded that improving electricity reliability positively impacts labor market outcomes of men and women in urban and rural areas in India. Together these studies outline the importance of understanding impacts of household electricity reliability, along with access to electricity, on economic outcomes.

2.2.3 Mechanisms driving the relationship between electrification and labor market outcomes

There are different ways in which access to reliable household electricity can affect labor demand and supply. This relationship can be driven by different mechanisms stemming from area and household electrification. Household access to reliable electricity can change the nature and amount of home production activities and the market.

Household electrification serves as a technological shock which has an ambiguous effect on home production activities (Becker, 1965). While household access to electricity improves the productivity of home production activities through investment in labor-saving devices and extends lengths of day, people might prefer to spend these hours on non-market or leisure activities. On the other hand, with longer hours of light, people might push leisure and non-market activities to the end of the day, hence increase labor supply for market activities (Dinkelman, 2011). Notwithstanding, wage and prices for market and domestic goods are significant mediators that can determine whether a person decides to spend their extended hours on market vs. non-market activities. These effects are likely to be larger in women who are traditionally seen to specialize in home production activities (Grogan and Sadanand, 2013; Khandker, Samad, et al., 2012).

Household access to reliable electricity can lead to creation of micro-enterprises, which can employ people from outside the household. Further, access to electricity can increase the marginal product of labor in the non-agricultural sector, which can create new employment opportunities (Rud, 2012). While mechanization of agriculture improve farm productivity, can increase, or decrease agricultural employment (Chakravorty, Emerick, and Ravago, 2016). This is likely to move employment from agricultural to non-agricultural sectors, especially in rural areas (Akpanjar and Kitchens, 2011). Additionally, household electrification is likely to stimulate area electrification, which can also increase labor demand by creation of new firms and businesses and growth of existing firms. Depending on the relationship between labor and technological inputs this may have an ambiguous effect on labor demand. Electrification of areas may induce migration, in which case the labor supply changes can be attributed to migration. To isolate the effect of access to reliable electricity on employment, it is important to understand what happens to home production activities, labor market, firms, micro enterprises, wages and migration. Data constraints restrict the analysis in this paper to examine labor markets. This investigation examines whether access to reliable household electricity increases market employment through a gendered lens in rural, urban, and slum households.

2.3 Background

2.3.1 Electrification in India

India has made remarkable progress towards ensuring access to affordable, secure and cleaner energy for its population over the last decade. Over 750 million Indian citizens gained access to electricity between 2000 and 2019 and its national electricity access rate increased from 43 percent in 2000 to 95 percent in 2019 (IEA, 2020). In 2018, the Government of India (GoI) reported 100 percent village electrification and in March 2019, the GoI announced that it had achieved full electrification of households. Even with such tremendous strides in electrification over 100 million people in India do not have access to electricity (IEA, 2020). The difference in these numbers is primarily due to the official definition of village electrification in India. Officially a village is considered electrified if at least 10 percent of the households are connected to the grid and local community facilities are grid connected.

Electricity policy and programs passed by the Government of India have helped rapidly increase village electrification in India. One of the key objectives of the “Electricity Act”, a major piece of legislation passed in the electricity sector, in 2003 was to electrify all villages and habitations with more than 100 people. The program, Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY), implemented in 2005, aimed to enhance electricity access in over 400,000 village and connect more than 23 million households, thus placing a high impetus on household electrification. Despite high electricity access rates, reliability of power supply varies considerably. World bank reported a SAIDI rate of 3.17 and SAIDI rate of 2.38 for India in 2019. This implies that the average total duration of outages experienced by a customer in a year is 3.17 hours, and the number of service interruptions experienced by a customer in a year is 2.38 (World Bank, 2019). Utility reported data through these metrics may provide underestimated outages. (Ayaburi et al, 2020).

Table 2.1: Labor market of India, Source: 2017-2018

	Rural	Rural Men	Rural Women	Urban	Urban Men	Urban Women	Total
Worker population ratio¹	35	51.7	17.5	33.9	53	14.2	34.7
Unemployment rate²	6.1	5.8	3.8	7.8	7.1	10.8	5.3
Category of employment (%)							
Self-employed	57.7	57.8	57.7	32.4	39.2	34.7	38.3
Wage/Salary earners	13.1	14	10.5	41.4	45.7	52.1	47
Casual workers	29.1	28.2	13.1	11.8	15.1	13.1	14.7

2.3.2 Labor Markets in India

India has a large informal labor economy. In 2017-2018 the National Sample Survey Office (NSSO) reported 38.3 percent of the total labor market in India consisted of informal labor. The informal economy forms almost 57.7 percent and 32.4 percent of the rural and urban labor market respectively. This informal economy includes workers who are independent workers and helpers in family enterprises.

Urban areas have larger percentages of wage earners (41.4 percent) as compared to rural areas (13.1 percent). A high percentage of employed workers in rural India include casual workers (29.1 percent) who work on their own farms or other farms. Similar trends are seen for men and women in rural and urban labor markets.

2.4 Methodology

2.4.1 Data

The research uses a panel dataset jointly developed by University of Maryland and the National Council of Applied Economic Research (NCAER) in New Delhi which captures a variety of human development indicators and is nationally representative. The dataset was collected through surveys completed in the year 2004-05 and 2011-12. The 2004-05 surveys interviewed 41,554 households, in 1,503 villages and 971 urban neighborhoods across India. In 2011-2012, 83 percent of the households were interviewed again. Surveys for the dataset

were completed through two one hour interviews. The dataset contains individual and household level data, along with village infrastructure data where applicable. We use data from 39,930 households from this dataset who provided valid data for labor market outcomes used for our analysis.

In the data analyzed (see Appendix A), access to electricity increases in the rural households from 65.5 percent in 2005 to 80.9 percent in 2012. During the same timeframe supplied hours of electricity increase from about 9.5 hours to 11.08 hours in rural households. Urban and slum households enjoy high rates of access at 95.1 percent and 97 percent in 2005 and 2011-12 respectively for urban households, and 86.6 and 97 percent in 2005 and 2011-12 respectively for urban slum households. Urban households had 17.76 and 17.2 hours of electricity supplied daily for 2005 and 2011-12 respectively, while urban slums hours of electricity changed from 16.3 to 18.6 hours from 2005 to 2011-12.

2.4.2 Empirical Strategy

Nonrandom community or household selection for electrification can cause endogeneity. Electrification programs may be targeted towards areas having economic advantages such as easy road accessibility and a greater growth potential. Ignoring this endogeneity can lead to biased estimations. Electrification may be endogenous to labor market outcomes, which can cause an omitted variable bias. Further, once an area is connected, economically disadvantaged areas may have higher load shedding, thus affecting electricity reliability. Non-random electrification adoption at the household level is also possible when households with better labor market outcomes have higher electricity demands and are more likely to be connected to the grid leading to reverse causality.

Our conceptual model captures the effect of household electrification access and reliability on labor market outcomes as the key parameter of interest. We control for district and time fixed effects, as well as household and village level controls. In order to better obtain plausibly exogenous variation in household electrification, we use unusual variation in the mean access and reliability of household electrification in a community,

while excluding the household itself, and employ two underlying methodological approaches: panel fixed effects and instrumental variables. Although these are both conceptually straightforward research designs, several features of our data present complications. In this section we discuss these complications and our approaches to resolve them.

In this paper we examine two labor market outcomes: employment participation rate and number of hours worked per month. The variables of interest are a household’s access to electricity (Does a household have access to a grid electric supply?) and the reliability of the electric supply (How many hours of electricity supply does a household receive every day?)

The base model which estimates the causal effect of the household’s electricity access status and its electricity supply reliability on labor market outcomes for household members is given by equation 2.1 and 2.2. The subscripts h, c, d, and t denote household, village/community, district and time respectively.

$$Y_{ht} = \alpha + \delta_t + \delta_d + \delta_h + \beta Access_{hct} + \gamma X_{hct} + \varepsilon_{hct} \quad (2.1)$$

$$Y_{ht} = \eta + \theta_h + \theta_t + \theta_d + \mu Reliability_{hct} + v X_{hct} + \epsilon_{hct} \quad (2.2)$$

Y_{ht} equation 2.1 and 2.2 denotes the outcome variable i.e. labor participation rate or number of hours worked by individuals in a household h and time t. $Access_{hct}$ denotes a binary variable which indicates access to electricity of a household (1 for households with access to electricity and 0 for households without access to electricity). $Reliability_{hct}$ in equation 2.2 denotes a continuous variable which indicates number of hours of reliable electricity received by a household (0 to 24 hours in a day). X_{hct} in equation 2.1 and 2.2 is a vector of covariates which includes household observed characteristics. Control variables used in the models are household size; house-ownership; asset ownership; access to piped water and flush toilets, regional market price of rice, household head education, caste, household poverty levels, and number of children in the household. These controls were

selected based on existing literature (Chakravorty et al., 2014; Khandker, Samad, et al., 2012). ε_{hct} and ϵ_{hct} is the random error term.

Two separate regressions are used to estimate the effect of access of reliable electricity as described by equations 2.1 and 2.2. The constant variable α and η , controls for unobserved characteristics of a household. The variables δ_t , δ_d , δ_h , θ_h , θ_t , and θ_d represent household, time, and district fixed effects. Household fixed effects are time invariant characteristics of households. District time fixed effects are time invariant characteristics of districts.

If unobserved characteristics do not vary with time and are correlated with both household access to electricity and labor market outcomes, a panel fixed effects model can control for them since we compare the outcomes for the same households over time. However, if the unobserved characteristics are time varying, then a fixed effects model will also produce biased results.

2.4.3 Instrumental variables

The literature evaluating the effects of electrification frequently employs the instrumental variable empirical approach to deal with the endogeneity problem of household electrification (Chakravorty et al., 2014, Dinkelman, 2011; Khandker, Samad, et al, 2012; Rao, 2013). The instrumental variables should produce exogeneous variation in access to electricity and the reliability of electricity. We use average household electricity access and hours at the village level excluding the household itself, as an instrument to address the existing endogeneity. It measures the household level variation temporally which permits us to consider the time-variant unobserved heterogeneity for the panel dataset. This instrument has been previously used in literature by Khandker, Samad, et al. (2012) and Rao (2013).

The 2SLS fixed effects model is used in the analysis. Fixed effect Instrumental Variables (FE-IV) is robust to correlations between unobserved effects and explanatory and instrumental variables. The two-stage estimation using the instrumental variables

approach is given by:

$$Access_{hct} = \theta_0 + \theta_1 IV_{ct} + \gamma X_{hct} + \delta_t + \delta_d + \delta_h + \varepsilon_{1hct} \quad (2.3)$$

$$Reliability_{hct} = \vartheta_0 + \vartheta_1 IV_{ct} + v X_{hct} + \theta_h + \theta_t + \theta_d + \varepsilon_{2hct} \quad (2.4)$$

IV_{hct} is the instrument used which includes two instruments in our estimations i) average electricity access of a household h 's village or community c at time t ii) average household electricity hours of a household h 's village or community c at time t . θ_1 and v_h is the coefficient of the instrument. All other variables and specifications remain the same as in the baseline estimation in equation 2.1 and 2.2. The instrument we select for identification should explain a household's decision to be connected to the electric grid or the increase in the demand for the hours of electricity. Also, this instrument should not explain the outcome variables of interest.

Once a village has access to electricity, peer pressure or demonstration effect is likely to affect a household's decision to obtain access to electricity. If neighbors of a household obtain access to electricity, a household is likely to follow their neighbors in the village since, a lack of access to electricity can indicate a lower socioeconomic standing which a household would prefer to avoid if they are able to afford it (Khandker, Barnes, et al., 2012). Influence of social networks and peer effects on household decision making is well demonstrated in literature. A vast literature reviews the role of peer effects in new technology adoption in developing countries, especially as related to agricultural, health, and education household decisions. Broadly, this literature has found there to be strong influence of peer effects, especially in new technology adoption across sectors (Conley and Udry, 2010; Oster and Thornton, 2012; Bandiera and Rasul, 2006). More specifically, there is growing literature on the role of social spillovers or how the decisions of a household's neighbors, social network, or friends influence in the context of energy related choices (Bernard and Torero, 2015; Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Srinivasan and Carattini, 2020). Akerlof and Kranton (2002) studied educational outcomes and analyzed peer effect in schooling decisions, while Bandiera and Rasul (2006)

Table 2.2: First Stage OLS regression

	Rural		Urban		Slums	
Variables	Access	Hours of electricity	Access	Hours of electricity	Access	Hours of electricity
Village mean access to electricity	0.736***	-3.170***	0.271***	-11.374***	0.579***	-7.145***
Village mean hours of electricity	-0.002***	0.946***	0.001	0.959***	-0.002	0.863***
Observations	23,931	23,931	14,309	14,309	1,690	1,690
R-squared	0.512	0.627	0.245	0.626	0.493	0.662

explored the effect of social networks on technology adoption in Mozambique. Within the energy context, Srinivasan and Carattini (2020), found strong social peer effects in a household’s decision to use liquefied petroleum gas (LPG) in India. Also, in Ethiopia, Bernard and Torero, 2015 found that a neighbors’ connection behavior had large positive effects on a household’s electricity connection decision. The existing literature provides strong evidence that the higher the proportion of connected households in a village, the higher the possibility that a household living in that village will adopt electricity if they are able to afford it.

A valid instrument needs to satisfy two conditions: that it is correlated to the endogenous regressor $Cov(IV, AccessorReliability) \neq 0$, and that it is not correlated to the error term $Cov(IV, \epsilon) \neq 0$. Regarding the first condition, the results of the first stage regressions in Table 2.2 show a strong correlation between the IV and the endogenous variables. Further, we have also formulated the first-stage F-statistics for the regressions of our main specification and these were found to cross the threshold in all specifications to ensure validity of the instrument. The average village electrification rate is 0.7 with a standard deviation of 0.3 in rural areas in 2005, and it is 0.8 and 0.4 respectively in 2012, showing that there is substantial variation in household access at the village level.

The key exclusion restriction needed for a good instrument is that neighborhood mean

access to household electrification and electrification reliability, excluding the household itself, does not affect household labor market outcomes directly, and that neighborhood access and reliability variations do not result from something that directly impacts household labor market outcomes. The exogeneity condition for the instrument holds because electricity availability in the neighborhood should not directly affect the labor market supply of a household, which should be determined by household characteristics (Khandker, Samad, et al., 2012, Rao, 2013). Market conditions can however influence labor demand. To represent the market, we include the regional market price for rice as a primary proxy for market prices and market conditions. Being a basic commodity that most households purchase, these prices are reflective of local labor market conditions (Rao, 2013). Further, controlling for market conditions through the market price of rice we account for local spill-over effects at the village and district level (electrification in own village could be correlated with higher labor force participation through, for example, higher economic activity).

While discussing this empirical strategy, it is important to note that we do not identify the average effect of electrification or of electricity reliability across all households with our instrument. Instead, we identify a local average treatment effect where θ_1 and v_1 (the coefficient of the instrument) represent the effect of household electrification and electricity reliability only in villages that have the same electrification rates and reliability as when the model predicts (Imbens and Angrist, 1994). While we can identify causal effects only for this specific group of compliers, such identification is only a concern in the face of treatment effect heterogeneity.

There are several threats to our current estimation strategy which need to be addressed to identify a robust relationship between labor market outcomes and access to reliable electricity. Our identification strategy would fail to account for time varying unobserved characteristics of electrification, if our instruments are not exogeneous. Electrification rates at the local level could have potential general equilibrium effects on labor market outcomes. Non random grid placement at the village level could result in differential

employment growth and omitted variable bias in our estimations. We argue that the instrument i.e. mean access or hours of electricity of a neighborhood, excluding the household, does not affect the labor market outcomes of a household directly, particularly after controlling for other household and community characteristics. Because we include district fixed effects, we are able to control for local, unobserved district fixed effects. We control for regional market conditions through a basic commodity price i.e., price of rice. Also, since we have two instruments for one endogenous variable, we can perform the overidentifying test, which shows the instruments are valid together in most specifications.

We performed several tests on our instruments to test our identification strategy. A number of tests for instrument validity for electrification access and electricity reliability variables, were performed and reported. A test for under identification was performed which examines whether the instruments are correlated with the endogenous regressor(s). The test is implemented by Kleibergen-Paap's LM statistic, under the null hypothesis that the equation is under-identified, that is, instruments do not affect the endogenous variables significantly. As shown in the results section, the null hypothesis is rejected for all our specifications, that is, the instruments are relevant. We also computed values for the Sargan test which tests the overidentifying restrictions specified by an overidentifying model. It allows us to test whether the excluded instruments are appropriately independent of the error process. The null hypothesis of the test is that the over identified restrictions are valid. All our main specifications fail to reject the null, except for the regression which measures the effect of electricity reliability on labor hours in male rural populations, and the regression which measures the effect of electricity access on labor hours in male urban populations. The Montiel Pflueger F test statistic tests the null hypothesis that the instruments are weak. Checking against the threshold values for the test we found that all our main specifications rejected the null hypothesis (Pflueger and Wang, 2015).

2.5 Results

The results of the impact of electricity access and hours of electric supply on labor market outcomes have been presented in Tables 2.3 to 2.11. Table 2.3 and Table 2.4 presents results for the full sample of households from for rural, urban, and slum populations, with IV fixed effects specifications for labor participation rates and labor hours respectively. Tables 2.5 through 2.10 represent IV fixed effects results for men, women and total populations in rural, urban and slum areas with electricity access and electricity reliability as dependent variables. All result regression specifications have district and year fixed effects along with additional independent variables as described in the empirical model. Robust standard errors are calculated for all coefficients. Our main estimations in tables 2.5 through 2.10 have been estimated with only electrified households for the electricity reliability dependent variable, however, as a robustness check, we also estimated these results on the full sample of electrified and non-electrified households in table 2.11. This serves as a robustness check, since only electrified households does not consider a majority of poor households, especially in rural areas, that do not have electricity.

2.5.1 Regional results

Table 2.3 evaluates the local average effect of household electricity access on labor participation rates and labor hours in rural, urban and slum populations. Similarly, Table 2.4 evaluates the local average effect of household electricity reliability on labor participation rates and labor hours in total rural, urban and slum populations. In table 3, columns 1, 3 and 5 use labor participation as the dependent variable, while columns 2, 4 and 6 use labor hours as the dependent variable for total rural, urban and slum populations. Similarly in table 2.4, electricity reliability is the treatment variable and columns 1, 3 and 5 use labor participation as the dependent variable, while columns 2, 4 and 6 use labor hours as the dependent variable for total rural, urban and slum populations. These tables also present the coefficients on all the control variables used in

the estimations. District time fixed effects are also included in these regressions in table 2.3 and 4.

Table 2.3: Impact of electricity access on labor participation and hours in all populations

	(1)	(2)	(3)	(4)	(5)	(6)
	Rural-LP	Rural-LH	Urban-LP	Urban-LH	Slum-LP	Slum-LH
Access	-0.0374* (0.0168)	66.57 (35.46)	-0.0467 (0.122)	225.2 (306.2)	-0.0899 (0.143)	-58.53 (295.6)
Household assets	-0.0115*** (0.00092)	-12.4*** (2.005)	-0.0116*** (0.00201)	-20.3*** (5.090)	-0.00993* (0.00458)	-11.91 (10.16)
House ownership	0.0191 (0.0120)	-115*** (27.57)	-0.0418*** (0.00725)	-171*** (18.55)	-0.0446* (0.0188)	-91.68 (46.99)
No of persons in a household	-0.0066*** (0.00115)	-20.2*** (2.455)	-0.00624*** (0.00139)	-15.2*** (3.402)	-0.00903* (0.00444)	-27.94* (11.57)
Market price of rice	0.00660 (0.0320)	-36.58 (67.45)	-0.00296 (0.0243)	-3.617 (69.87)	-0.0541 (0.167)	-33.14 (374.9)
Access to water	-0.00310 (0.00573)	15.11 (12.88)	-0.0149* (0.00635)	-38.66* (15.93)	0.0493** (0.0189)	53.97 (48.65)
Access to toilets	-0.0523*** (0.00953)	-50.74* (20.51)	0.0115 (0.00647)	63.24*** (16.63)	0.00345 (0.0208)	50.67 (53.39)
Household head education	-0.0053*** (0.00054)	-2.192 (1.186)	-0.00231** (0.000758)	0.525 (1.860)	-0.0110*** (0.00205)	-20.3*** (5.015)
Poverty	-0.0106* (0.00534)	-28.21* (11.34)	0.00777 (0.00836)	-8.715 (20.13)	-0.0136 (0.0192)	-44.73 (46.56)
Number of children	0.0103*** (0.00157)	23.05*** (3.446)	0.00517* (0.00209)	11.85* (5.182)	0.00533 (0.00617)	26.63 (15.47)
Number of observations	23931	23931	14309	14309	1690	1690
R-squared	0.0561	0.0242	0.0656	0.0373	0.0837	0.0434
First stage F-statistic	1555.6	1555.6	33.29	33.29	19.88	19.88
Montiel Pflueger F statistic	1812.8	1812.8	50.79	50.79	25.48	25.48
District-Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.3 shows us that an increase in electricity access has a weakly significant negative effect on labor participation in rural populations, and no significant effect on urban and slum populations. There is no significant effect of electricity access on labor hours in rural, urban and slum populations. Table 2,4 shows us that an improvement in electricity reliability increases labor participation rates and labor hours in urban

Table 2.4: Electricity access and reliability effects on labor participation rate in rural populations

	(1)	(2)	(3)	(4)	(5)	(6)
	Rural-LP	Rural-LH	Urban-LP	Urban-LH	Slum-LP	Slum-LH
Hours of electricity	-0.000435 (0.000700)	2.941 (1.618)	0.00261** (0.000889)	11.51*** (2.254)	0.00154 (0.00323)	6.750 (8.170)
Household assets	-0.0143*** (0.000750)	-10.74*** (1.698)	-0.0120*** (0.000839)	-17.22*** (2.074)	-0.0117*** (0.00251)	-16.53* (6.675)
House ownership	0.00377 (0.0130)	-160.0*** (31.46)	-0.0421*** (0.00679)	-175.8*** (17.48)	-0.0531** (0.0195)	-96.83 (50.04)
No of persons in a household	-0.00464*** (0.00131)	-15.48*** (2.863)	-0.00616*** (0.00138)	-14.39*** (3.411)	-0.0108* (0.00449)	-29.82* (12.01)
Market price of rice	-0.0382 (0.0345)	-83.15 (74.56)	-0.00182 (0.0235)	-19.01 (68.34)	-0.0419 (0.170)	57.25 (373.4)
Access to water	-0.00289 (0.00625)	7.029 (13.99)	-0.0134* (0.00642)	-40.75* (16.16)	0.0528** (0.0198)	59.04 (53.14)
Access to toilets	-0.0492*** (0.00992)	-49.01* (21.75)	0.0109 (0.00637)	52.53** (16.29)	0.00593 (0.0214)	72.10 (55.11)
Household head education	-0.00490*** (0.000619)	-1.097 (1.384)	-0.00239** (0.000769)	0.314 (1.898)	-0.0109*** (0.00219)	-21.73*** (5.387)
Poverty	-0.0158* (0.00650)	-35.48* (14.11)	0.00953 (0.00853)	-16.20 (20.75)	-0.00808 (0.0204)	-25.23 (51.52)
Number of children	0.00899*** (0.00178)	18.97*** (4.082)	0.00419* (0.00213)	10.44* (5.276)	0.00167 (0.00635)	17.67 (16.33)
Number of observations	17472	17472	13758	13758	1506	1506
R-squared	0.0658	0.0268	0.0604	0.0398	0.0906	0.0522
First stage F-statistic	9620.3	9620.3	3959.2	3959.2	231.7	231.7
Montiel Pflueger F statistic	6159.7	6159.7	3743.3	3743.3	242.8	242.8
District-Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

populations, while having no significant effect on rural and slum populations.

2.5.2 Gendered results

The results from the regional analysis conceal important heterogeneities across genders. We examine the gender specific effects of electricity access and reliability on labor participation rates and labor hours. These are presented across rural, urban and slum populations in Table 2.5 through Table 2.10.

2.5.2.1 Rural populations

For rural populations, Table 2.5 and Table 2.6 show effects of electricity access and reliability on labor participation rates and labor hours respectively. In table 2.5 and table 2.6, panel A shows coefficients on electricity access while panel B shows coefficients on electricity reliability across rural male, female and total populations. In table 2.5 from panel A, we find a drop in the labor participation rates of rural men with increased access to household electrification which is significant. Rural men see a drop of about 8 percent in their employment rate with increased electricity access. Total rural populations see a drop in labor participation rates with increased access to electricity, however this effect is weakly significant. In table 2.6, from panel A, we see no marginal effect of electricity access on labor hours in rural male, female and total populations. In table 2.5 and 2.6 from panel B, we do not find effects of electricity reliability on labor market outcomes of total, male and female rural populations. Female rural populations see a weakly significant drop of about 0.2 percent in labor participation rates with increased electricity reliability. The Montiel-Pueger F-stat is greater than the 5 percent critical value for all the regressions presented in these tables. This implies that we can reject the null of weak instrument for our IV regression for a weak instrument threshold of $\tau = 5percent$.

Thus, these results show that rural women, men and total populations do not see an improvement in labor market outcomes with access to reliable electricity. In fact, rural male populations see their participation rates drop slightly with increased access to electricity, and we see weakly significant negative effects of electricity access on total rural

populations labor market participation rates, and weakly significant negative effects of electricity reliability on rural female populations labor market participation rates. Thus, rural populations do not see improvements in household labor market outcomes from increased reliable electricity.

Table 2.5: Electricity access and reliability effects on labor participation in rural populations

	(1)	(2)	(3)
	Female	Male	Total
Panel A			
Access to electricity (0/1)	-0.0350 (0.0229)	-.0810*** (0.0216)	-0.0374* (0.0168)
Number of observations	23931	23931	23931
R-squared	0.0493	0.0156	0.0561
First stage F-statistic	1555.6	1555.6	1555.6
Kleibergen-Paap rk LM statistic	0	0	0
Cragg-Donald Wald F statistic	1723.0	1723.0	1723.0
Hansen J statistic p-value	0.0191	0.831	0.183
Montiel Pflueger F stat	1812.8	1812.8	1812.8
District-Time Fixed effects	Yes	Yes	Yes
Panel B			
Hours of electricity (0 to 24)	-0.00208* (0.000939)	0.000736 (0.000904)	-0.000435 (0.000700)
Number of observations	17472	17472	17472
R-squared	0.0564	0.0226	0.0658
First stage F-statistic	9620.3	9620.3	9620.3
Kleibergen-Paap rk LM statistic	0	0	0
Cragg-Donald Wald F statistic	8236.8	8236.8	8236.8
Hansen J statistic p-value	0.0538	0.897	0.220
Montiel Pflueger F stat	6159.7	6159.7	6159.7
District-Time Fixed effects	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows instrumental variable impacts of electricity access and reliability on labor market outcomes. Robust standard errors are used. Household and community controls are included in all regressions. These include education of the head of household; household size; house ownership; asset ownership; access to piped water and flush toilets; poverty of household, number of children in household, and market price of rice. Panel B uses electrified households only, whereas Panel A uses electrified and non-electrified households.

Table 2.6: Electricity access and reliability effects on labor hours in rural populations

	(1)	(2)	(3)
	Female	Male	Total
Panel A			
Access to electricity (0/1)	15.09 (34.30)	57.25 (49.73)	66.57 (35.46)
Number of observations	23931	23931	23931
R-squared	0.0299	0.0186	0.0242
First stage F-statistic	1555.6	1555.6	1555.6
Kleibergen-Paap rk LM statistic	0	0	0
Cragg-Donald Wald F statistic	1723.0	1723.0	1723.0
Hansen J statistic p-value	0.615	0.0537	0.0808
Montiel Pflueger F stat	1812.8	1812.8	1812.8
District-Time Fixed effects	Yes	Yes	Yes
Panel B			
Hours of electricity (0 to 24)	0.615 (1.633)	4.182 (2.307)	2.941 (1.618)
Number of observations	17472	17472	17472
R-squared	0.0302	0.0223	0.0268
First stage F-statistic	9620.3	9620.3	9620.3
Kleibergen-Paap rk LM statistic	0	0	0
Cragg-Donald Wald F statistic	8236.8	8236.8	8236.8
Hansen J statistic p-value	0.129	0.00186	0.109
Montiel Pflueger F stat	6159.7	6159.7	6159.7
District-Time Fixed effects	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows instrumental variable impacts of electricity access and reliability on labor hours. Robust standard errors are used. Household and community controls are included in all regressions. These include education of the head of household; household size; house ownership; asset ownership; access to piped water and flush toilets; poverty of household, number of children in household, and market price of rice. Panel B uses electrified households only, whereas Panel A uses electrified and non-electrified households.

2.5.2.2 Urban populations

For urban populations, Table 2.7 and Table 2.8 show effects of electricity access and reliability on labor participation rates and labor hours respectively. In Table 2.7 and Table 2.8, panel A shows coefficients on electricity access while panel B shows coefficients on electricity reliability across urban male, female and total populations. In table 2.7 and table 2.8 from panel A, we find no significant effects of increase in household electricity access on labor participation rates and hours on urban male, female and total populations. In table 2.7 and table 2.8 in panel B we see positive marginal effects of increase in electricity reliability on labor participation rates and labor hours of urban male and total populations.

From panel A in table 2.7, we see that urban women also have weakly significant positive effect of 0.2 percent increase in labor participation rates with improved electricity access. From panel B in table 2.7, we see that one more hour of electricity per day in urban areas can increase labor participation rates of male and total populations by approximately 0.3 percent for both populations. These effects are strongly statistically significant at 1 percent. In panel B of table 2.8, we see an increase in the number of hours worked by men and the total urban population by 18 and 12 hours per year respectively as an effect of increase in electricity reliability. These effects are significant at 0.1 percent. Similarly, urban women see a weakly significant increase of 5 hours per year in labor hours as an effect of improved electricity reliability. The Montiel-Pueger F-stat for the significant regression results is greater than the 5 percent critical value. This implies that we can reject the null of weak instrument for our IV regression for a weak instrument threshold of $\tau = 5percent$ for all urban population results.

2.5.2.3 Slum populations

For slum populations, Table 2.9 and Table 2.10 show effects of electricity access and reliability on labor participation rates and labor hours respectively. In Table 2.9 and Table 2.10, panel A shows coefficients on electricity access while panel B shows coefficients on

Table 2.7: Electricity access and reliability effects on labor participation in urban populations

	(1)	(2)	(3)
	Female	Male	Total
	Panel A		
Access to electricity (0/1)	-0.0737 (0.147)	-0.000384 (0.166)	-0.0467 (0.122)
Number of observations	14309	14309	14309
R-squared	0.0417	0.0272	0.0656
First stage F-statistic	33.29	33.29	33.29
Kleibergen-Paap rk LM statistic	3.97e-15	3.97e-15	3.97e-15
Cragg-Donald Wald F statistic	101.7	101.7	101.7
Hansen J statistic p-value	0.0564	0.283	0.387
Montiel Pflueger F stat	50.79	50.79	50.79
District-Time Fixed effects	Yes	Yes	Yes
	Panel B		
Hours of electricity (0 to 24)	0.00219* (0.00106)	0.00326** (0.00125)	0.00261** (0.000889)
Number of observations	13758	13758	13758
R-squared	0.0380	0.0272	0.0604
First stage F-statistic	3959.2	3959.2	3959.2
Kleibergen-Paap rk LM statistic	0	0	0
Cragg-Donald Wald F statistic	4914.8	4914.8	4914.8
Hansen J statistic p-value	0.337	0.540	0.853
Montiel Pflueger F stat	3743.3	3743.3	3743.3
District-Time Fixed effects	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

The table shows instrumental variable impacts of electricity access and reliability on labor market outcomes. Robust standard errors are used. Household and community controls are included in all regressions. These include education of the head of household; household size; house ownership; asset ownership; access to piped water and flush toilets; poverty of household, number of children in household, and market price of rice. Panel B uses electrified households only, whereas Panel A uses electrified and non-electrified households.

Table 2.8: Electricity access and reliability effects on labor hours in urban populations

	(1)	(2)	(3)
	Female	Male	Total
Panel A			
Access to electricity (0/1)	74.60 (281.1)	227.7 (451.3)	225.2 (306.2)
Number of observations	14309	14309	14309
R-squared	0.0243	0.0241	0.0373
First stage F-statistic	33.29	33.29	33.29
Kleibergen-Paap rk LM statistic	3.97e-15	3.97e-15	3.97e-15
Cragg-Donald Wald F statistic	101.7	101.7	101.7
Hansen J statistic p-value	0.0327	0.00101	0.0558
Montiel Pflueger F stat	50.79	50.79	50.79
District-Time Fixed effects	Yes	Yes	Yes
Panel B			
Hours of electricity (0 to 24)	5.071* (2.185)	17.50*** (3.509)	11.51*** (2.254)
Number of observations	13758	13758	13758
R-squared	0.0229	0.0271	0.0398
First stage F-statistic	3959.2	3959.2	3959.2
Kleibergen-Paap rk LM statistic	0	0	0
Cragg-Donald Wald F statistic	4914.8	4914.8	4914.8
Hansen J statistic p-value	0.788	0.380	0.277
Montiel Pflueger F stat	3743.3	3743.3	3743.3
District-Time Fixed effects	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

The table shows instrumental variable impacts of electricity access and reliability on labor market outcomes. Robust standard errors are used. Household and community controls are included in all regressions. These include education of the head of household; household size; house ownership; asset ownership; access to piped water and flush toilets; poverty of household, number of children in household, and market price of rice. Panel B uses electrified households only, whereas Panel A uses electrified and non-electrified households.

electricity reliability across urban slum male, female and total populations. In Table 2.9 and Table 2.10 from, we find no significant effects of increase in household electricity access and reliability on labor participation rates and hours of urban slum male, female and total populations. It is worth noting that studying Table 2.9 and Table 10 in panel B shows that it is likely that urban slum populations behave like rural populations and do not see benefits of electricity access and reliability on labor market outcomes.

Table 2.9: Electricity access and reliability effects on labor participation in slum populations

	(1)	(2)	(3)
	Female	Male	Total
	Panel A		
Access to electricity (0/1)	-0.108 (0.195)	-0.187 (0.198)	-0.0899 (0.143)
Number of observations	1690	1690	1690
R-squared	0.0581	0.00963	0.0837
First stage F-statistic	19.88	19.88	19.88
Kleibergen-Paap rk LM statistic	0.000000910	0.000000910	0.000000910
Cragg-Donald Wald F statistic	33.53	33.53	33.53
Hansen J statistic p-value	0.844	0.446	0.920
Montiel Pflueger F stat	25.48	25.48	25.48
District-Time Fixed effects	-0.108	-0.187	-0.0899
	Panel B		
Hours of electricity (0 to 24)	0.000582 (0.00473)	0.00559 (0.00472)	0.00154 (0.00323)
Number of observations	1506	1506	1506
R-squared	0.0518	0.0322	0.0906
First stage F-statistic	231.7	231.7	231.7
Kleibergen-Paap rk LM statistic	6.97e-34	6.97e-34	6.97e-34
Cragg-Donald Wald F statistic	383.0	383.0	383.0
Hansen J statistic p-value	0.884	0.363	0.578
Montiel Pflueger F stat	242.8	242.8	242.8
District-Time Fixed effects	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

The table shows instrumental variable impacts of electricity access and reliability on labor market outcomes. Robust standard errors are used. Household and community controls are included in all regressions. These include education of the head of household; household size; house ownership; asset ownership; access to piped water and flush toilets; poverty of household, number of children in household, and market price of rice. Panel B uses electrified households only, whereas Panel A uses electrified and non-electrified households.

Table 2.10: Electricity access and reliability effects on labor hours in slum populations

	(1)	(2)	(3)
	Female	Male	Total
	Panel A		
Access to electricity (0/1)	314.2 (294.6)	-644.8 (517.4)	-58.53 (295.6)
Number of observations	1690	1690	1690
R-squared	0.0251	-0.00632	0.0434
First stage F-statistic	19.88	19.88	19.88
Kleibergen-Paap rk LM statistic	0.000000910	0.000000910	0.000000910
Cragg-Donald Wald F statistic	33.53	33.53	33.53
Hansen J statistic p-value	0.810	0.182	0.571
Montiel Pflueger F stat	25.48	25.48	25.48
District-Time Fixed effects	Yes	Yes	Yes
	Panel B		
Hours of electricity (0 to 24)	0.925 (9.447)	21.23 (12.61)	6.750 (8.170)
Number of observations	1506	1506	1506
R-squared	0.0373	0.0318	0.0522
First stage F-statistic	231.7	231.7	231.7
Kleibergen-Paap rk LM statistic	6.97e-34	6.97e-34	6.97e-34
Cragg-Donald Wald F statistic	383.0	383.0	383.0
Hansen J statistic p-value	0.319	0.106	0.974
Montiel Pflueger F stat	145.4	242.8	242.8
District-Time Fixed effects	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

The table shows instrumental variable impacts of electricity access and reliability on labor market outcomes. Robust standard errors are used. Household and community controls are included in all regressions. These include education of the head of household; household size; house ownership; asset ownership; access to piped water and flush toilets; poverty of household, number of children in household, and market price of rice. Panel B uses electrified households only, whereas Panel A uses electrified and non-electrified households.

2.5.3 Robustness Check

As a robustness check, we also computed the results for electricity reliability with a full sample, i.e. a sample of electrified and non-electrified households for rural, urban and slum populations. These results are given in tables 2.11 through 2.13. These show similar effects to those seen in our main specification electricity reliability results.

Table 2.11: Impact of electricity reliability on labor participation and hours in rural populations for a full sample

	Female-LP	Male-LP	Total-LP	Female-LH	Male-LH	Total-LH
	(1)	(2)	(3)	(4)	(5)	(6)
Hours of electricity	-0.00240** (0.000868)	-0.00118 (0.000813)	-0.00138* (0.000629)	0.921 (1.461)	4.544* (2.003)	3.402* (1.422)
Number of observations	23931	23931	23931	23931	23931	23931
R-squared	0.0494	0.0191	0.0573	0.0300	0.0189	0.0253
First stage F-statistic	3932.8	3932.8	3932.8	3932.8	3932.8	3932.8
Kleibergen-Paap rk LM statistic	0	0	0	0	0	0
Cragg-Donald Wald F statistic	4263.1	4263.1	4263.1	4263.1	4263.1	4263.1
Sargan statistic	0.703	0.000619	0.155	0.882	0.900	0.394
Montiel Pflueger F statistic	4690.5	4690.5	4690.5	4690.5	4690.5	4690.5
District-Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows instrumental variable impacts of electricity access and reliability on labor market outcomes. Robust standard errors are used. Household and community controls are included in all regressions. These include education of the head of household; household size; house ownership; asset ownership; access to piped water and flush toilets; poverty of household, number of children in household, and market price of rice. The sample includes electrified and unelectrified households.

In table 2.11, row 1, we see an increase in significance of the marginal effects of electricity reliability on labor market outcomes in female, male and total populations. However, these effects remain weakly significant except for the case of labor participation rates of rural women. Rural women see a decrease in labor participation rates of 0.2 percent as an effect of an increase in electricity reliability. While this is a significant effect, the magnitude of the effect is rather small. We also see a weakly significant negative effect of electricity reliability on labor participation rates of the total population, and weakly significant positive effects of electricity reliability on labor hours in rural male and total populations, however, all of these effects show a very small magnitude. Thus, these results

Table 2.12: Impact of electricity reliability on labor participation and hours in urban populations for a full sample

	Female-LP	Male-LP	Total-LP	Female-LH	Male-LH	Total-LH
	(1)	(2)	(3)	(4)	(5)	(6)
Hours of electricity	0.00186 (0.00106)	0.00361** (0.00123)	0.00243** (0.000885)	4.643* (2.184)	18.48*** (3.464)	11.33*** (2.233)
Number of observations	14309	14309	14309	14309	14309	14309
R-squared	0.0409	0.0266	0.0639	0.0241	0.0242	0.0383
First stage F-statistic	2796.8	2796.8	2796.8	2796.8	2796.8	2796.8
Kleibergen-Paap rk LM statistic	0	0	0	0	0	0
Cragg-Donald Wald F statistic	2937.5	2937.5	2937.5	2937.5	2937.5	2937.5
Sargan statistic	0.372	0.515	0.325	0.821	0.480	0.722
Montiel Pflueger F statistic	1846.1	1846.1	1846.1	1846.1	1846.1	1846.1
District-Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows instrumental variable impacts of electricity access and reliability on labor market outcomes. Robust standard errors are used. Household and community controls are included in all regressions. These include education of the head of household; household size; house ownership; asset ownership; access to piped water and flush toilets; poverty of household, number of children in household, and market price of rice. The sample includes electrified and unelectrified households.

Table 2.13: Impact of electricity reliability on labor participation and hours in slum populations for a full sample

	Female-LP	Male-LP	Total-LP	Female-LH	Male-LH	Total-LH
	(1)	(2)	(3)	(4)	(5)	(6)
Hours of electricity	-0.00133 (0.00491)	0.00320 (0.00496)	-0.000641 (0.00337)	3.402 (9.819)	15.55 (13.11)	4.621 (8.485)
Number of observations	1690	1690	1690	1690	1690	1690
R-squared	0.0588	0.0305	0.0881	0.0382	0.0294	0.0451
First stage F-statistic	103.1	103.1	103.1	103.1	103.1	103.1
Kleibergen-Paap rk LM statistic	1.50e-25	1.50e-25	1.50e-25	1.50e-25	1.50e-25	1.50e-25
Cragg-Donald Wald F statistic	121.9	121.9	121.9	121.9	121.9	121.9
Sargan statistic	0.604	0.293	0.546	0.316	0.145	0.775
Montiel Pflueger F statistic	103.4	103.4	103.4	108.7	103.4	103.4
District-Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows instrumental variable impacts of electricity access and reliability on labor market outcomes. Robust standard errors are used. Household and community controls are included in all regressions. These include education of the head of household; household size; house ownership; asset ownership; access to piped water and flush toilets; poverty of household, number of children in household, and market price of rice. The sample includes electrified and unelectrified households.

are primarily consistent with our conclusions that rural populations, male and female, do not see improved labor market outcomes with an increase in electricity reliability. The differences we see in our results is likely since when considering only electrified households as in the main specification, we are not considering a majority of poor households, especially in rural areas, that do not have electricity.

In table 2.12, we see the effects of electricity reliability on labor market outcomes in urban populations., which are similar in magnitude, direction, and significance to the main specification. In table 2.13, we see the effects of electricity reliability on labor market outcomes in slum populations, which like our main specification, are insignificant. Weakly positive effects of electricity reliability on labor participation rates of urban female populations lose significance in the robustness check. However, our conclusions remain the same, that electricity reliability improves labor market outcomes for urban male and total populations, however the magnitude of these changes is rather small. In table 2.13 we see that the effects of electricity reliability on labor market outcomes of slum populations remain insignificant.

2.6 Discussion

Our results show limited benefits of access to reliable electricity on labor market outcomes of rural, urban and urban slum, male and female populations. Rural male populations see a decline in labor participation rates with increased access to electrification, while we do not see significant effects of electricity reliability in a household on labor market outcomes in rural – male, female and total populations. Urban populations do not show significant effects of access to household electrification on labor market outcomes, while electricity reliability leads to improved labor market outcomes in urban populations, however, the magnitudes of these effects are small. We do not see significant effects of electricity access and reliability on urban slum populations. We also observe that reliable electricity results in larger gains for male populations versus female populations, especially in urban areas.

In India, agriculture is the primary occupation in rural areas. With access to electricity at the household level, it is likely that household operated farms also receive access to electricity. This access to electricity can facilitate irrigation, increase dry season cropping intensity or mechanize post-harvest operations such as crop threshing. While access to electricity in farms can improve farm productivity, it can also increase or decrease employment in agriculture due to agricultural mechanization. Men and women often work as farm helpers, especially in family-owned farms in rural areas, and it is possible that with the advent of reliable electrification, this role may be reduced which can lead to reduction of labor participation for men and women (Chakravorty et al., 2016).

Vast literature evaluating gender differences in labor participation has shown that women specialize in unpaid domestic and care work, while men specialize in paid market work. Thus, majority of housework and family care is done by women, who end up spending less time working in the market (Berniell and Páramo, 2011; Duflo, 2012; Matulevich and Viollaz, 2019; Seymour, Malapit, and Quisumbing, 2017). Further, often women work more hours in total than men when productive activities such as market work, housework and unpaid family and childcare are considered altogether (Berniell and Páramo, 2011; Matulevich and Viollaz, 2019). While these findings may vary in degree across countries, regions and times, the conclusions have been consistent (Matulevich and Viollaz, 2019). These differences are found to be greater in rural areas as compared to urban areas across countries. Economic development can act as a tool to free time of women which can be used for market activities (Duflo, 2012). Lack of access to electricity can be a potential barrier to reducing gender disparities.

While electrification can free up time for women by improving home productivity, which can be used for market or other activities, our findings do not show significant positive effects of access to electrification on rural and urban female labor markets, like some recent research (Chakravorty et al., 2016; Burlig and Preonas, 2016; Lee et al., 2021, Lenz et al., 2017). Thus, we can see that freeing up time from housework may not be sufficient to help women participate in market activities and may be context driven. These

effects may be driven by several factors including parenthood (Maurer-Fazio and Connelly, 2017), gender norms and policy environments (Gornick and Meyers, 2003), a lack of opportunities for women in the labor markets in rural and urban areas in India or due to the constraints of family and childcare responsibilities of women which do not significantly change with access to electricity.

We do not see significant effects of access to household electrification in cities. From our descriptive statistics we can see that urban areas have high access to electricity (over 86 percent in 2005 and 97 percent in 2012), while the average hours of electricity received by an urban household can be improved substantially (approximately 16 hours in 2005 and 18 hours in 2012). With high electricity access rates in cities, there is limited variation amongst electrified and unelectrified households. Thus, we do not see significant effects of access to household electrification in cities. Also, we can see that with high electricity access rates, reliability helps to improve labor market outcomes, however, even these improvements are small in magnitude i.e., less than one percent increase in labor participation rates across all populations, and labor hours are increased across populations by less than a day or 20 hours, over the period of a year. Reliable electrification generally benefits urban men more than urban women in our samples, however the effects on urban women are weakly significant.

The lack of significant effects of electrification on labor market outcomes of slums as per our model may be attributed to the small sample size of slums, which does not produce sufficient variation. Further, urban slums make up 5 percent of the Indian population, while the IHDS sample is not representative of this sample. Additionally, low variation in the endogenous variable i.e., access to electricity can lead to insignificant results seen in some of these estimations.

The only other literature which evaluates impacts of electricity reliability on labor market outcomes in our knowledge is Sedai et al., 2021. We believe that these are complementary studies, and some lessons can be learned by a comparison of the two studies. First, both studies examine different local average treatment effects in the data.

Since our instruments are means at the village level with exclusion of the household under consideration, our treatment effect comes from comparing average household outcomes across villages with different average treatment levels, and within the village, different household neighbor comparisons. Sedai et al., 2021 uses an instrument which uses electricity reliability means at the state level, while excluding the district of the individual's household, thus their treatment effect comes from comparing average individual outcomes across states with different average treatment levels, and within the state, different district comparisons.

Their study has different results as compared to ours which show positive improvements in labor market outcomes of male and female rural and urban populations with the advent of reliable electricity. These differences in results arise due to heterogeneous electrification treatment effects. The effects of household electrification depend on what household members can do with electricity, and this can lead to impacts which can vary across local regions in the same country or even across individuals within the same society (Lee, Miguel, et al., 2020). The different local average treatment effects captured by our studies result in varying results.

The local average treatment effect identified by both studies is the causal effect of the “complier population”. The complier population for the instrument used by Sedai et al., 2021, consists of districts that have electricity reliability which either matches the state mean electricity reliability or are interconnected with districts that match the state mean electricity reliability. It does not capture effects experienced by the “always taker/never taker populations” i.e., (in the case of Sedai et al., 2021) districts which do not follow the state average reliability metrics, or districts which do not improve reliability when their neighboring districts increase electricity hours. These districts could potentially be identified as districts that are lagging the rest of the state in terms of economic growth and development. The “complier population” for the instrument used in our research includes households that match the village mean electricity reliability. These villages could potentially be in districts that are in the “always taker/never taker populations” of the

Sedai et al., 2021 instrument. When we include these villages in our research, the positive gender effects of reliability for rural women and urban women that Sedai et al, 2021 find in their research reduce, and thus we have different results for similar populations that were examined. This implies that if a district is as economically developed as the state itself, it is able to leverage the infrastructure opportunities the state offers and has better labor market outcomes with improved infrastructure (electricity access and reliability). However, if there are districts that are not as economically developed as the rest of the state, the households in these districts might not fully benefit (in terms of labor market outcomes) from the electricity reliability in their village and district.

2.7 Conclusion

In this paper, use a nationally representative panel survey from IHDS, to evaluate the effect of household electricity access and reliability on labor market outcomes of a household. The development literature includes a large body of work which evaluates benefits of access to electricity, and more specifically, for rural populations. Yet there is limited literature evaluating the effects of electricity reliability. With this research we address this gap by evaluating the causal relationship between access to electricity and quality of electrical supply, and labor market outcomes, particularly labor participation rates and hours worked through a gendered lens in rural, urban and urban slum populations across India. This study contributes to the literature in understanding the heterogeneous impacts of household electricity access and reliability across regions with different economic compositions and across genders and has four main conclusions.

Firstly, we find that access to electricity does not improve labor market outcomes for urban, rural and urban slum areas. Secondly, we find that electricity reliability had more positive significant impacts in urban populations as compared to rural and urban slum populations where electricity reliability did not have any significant impacts on household labor market outcomes. Thirdly, we also find that men benefit more than women from electricity reliability with improved labor market outcomes in the urban contexts, whereas

male labor participation rates reduce with increase in access to electricity in rural areas. Lastly, comparing with literature on the topic, we find that for households to fully benefit from the true potential of electrification and reliability, their geographic location is important. If a household lies in a district which is as economically developed as the state it is situated in at average, the household is more likely to fully benefit from electrification and reliability of a community, as compared to a household, which may lie in a district which is not as economically developed as the state it lies in.

These results help highlight that investments in household electrification programs alone, might not be sufficient to spur economic growth especially in low- and middle-income countries. However, rigorously detecting potential drivers and effects of electrification programs, while recognizing the heterogeneity in these effects, is a possible future research path and key in developing our understanding of the role of electrification in economic development.

CHAPTER 3
EFFECTIVE RECIPROCITY IN ONLINE LABOR MARKETS?
PROTECT

3.1 Introduction

Contracts that fail to account for every possible contingency are considered "incomplete." Inefficiencies that may occur due to the inability of two parties to execute a complete contract have been studied extensively in economics. Labor market contracts between the employer and employee are often incomplete and do not capture what an employer may really care about i.e., worker performance. Short term online transactions in the labor market are growing which could make it harder to solve incomplete contracting problems. Therefore, this market structure provides the background for studying a bigger problem in labor markets - How can parties to a bargain improve efficiencies on an incomplete contract? We study this question within the context of online labor markets. More specifically, our paper answers the following question - What creates effective reciprocity in online labor exchange?

This has been studied and explained previously in literature using the gift exchange model. According to the theory of labor contracts as "gift exchange", employers may pay more than the market will bear for labor services in order to reinforce norms in which workers provide more than the minimum effort and high-quality work above the minimum contractual (Akerlof, 1982). Kube, Marechal, and Puppe (2012) generalized this concept to a broader sense of both monetary and nonmonetary reciprocity between employers and workers that goes beyond the letter of a contract. That is workers should respond to higher wages by increasing their effort and quality (positive reciprocity) and to lower wages levels by decreasing their effort and quality (negative reciprocity). This implies that if employers offer higher than market clearing wages, they are awarded by greater employee effort and quality. Every possible contingency in a working relationship can't be spelled out in law or contracts, so informal reciprocity or "gift exchange" can induce good treatment on both

sides (Akerlof, 1982, and Kube, Marechal, and Puppe, 2012). The specific context of our research setting is the following. Online labor markets are places where people exchange their labor for money, the goods produced by that labor are supplied via the internet, and the distribution of labor and money is decided by a group of buyers and sellers acting within a set of pricing rules. The current design of online labor markets does not adequately support crowd workers, job seekers, or the healthy expansion of these online labor markets due to three key issues: 1. Workers endure bad treatment and low compensation; 2. they have little incentive to create high-quality work in these environments; and 3. platforms do not match workers to the ideal assignments for their skill sets. Due to these structural design issues, often online labor markets do not cultivate the trust and reciprocity, which is more commonly found in the common workplace.

To answer our research question, we conduct an economic experiment in an online crowdsourcing platform which allows workers to enter flexible, short-term agreements to provide on-demand services. A dominant example of such a platform, which we use in our experiment is Amazon’s Mechanical Turk (MTurk) market for data entry, surveys, and Human Intelligence Tasks (HITs) that provide training data for artificial intelligence programs. We recruit crowd workers to perform a single task, while changing the compensation structure for different treatments. We use tasks with two types of sub tasks—ambiguous and unambiguous. Unambiguous subtasks refers to tasks that are simple and not tedious to complete, thus requiring low worker effort, cognitive ability and skill. An example of such a task in our experiment required workers to evaluate a company’s sustainability report to identify the company name and year of the report which were typically presented on the cover of the report. On the other hand, an example of an ambiguous task would be a worker reviewing the same report to find information on the company’s renewable energy goal. This information is often present in the report in a non-standard format, which makes the task relatively difficult and time consuming, requiring more worker effort, cognitive ability, and subjective judgement for completion. By using ambiguous and unambiguous subtasks, we are able to measure contractable and

non-contractable dimensions of data quality (i.e., accuracy and validity). Ambiguous tasks help us to evaluate non-contractable dimensions of accuracy and validity, which cannot be done to the same degree using unambiguous tasks. Further, it enables us to also vary task complexity to test the importance of matching a worker’s skill to the task at hand alongside incentives and gifts for performance.

We use a 2x5 experimental design, where we use 2 framing treatments, and 5 payment treatments which are designed to test the gift exchange hypothesis by varying the compensation structure across the treatments. The 2 framing treatments – one guarantees that the completed work will be accepted, while the other does not.¹ While the 5 payment treatments offer a baseline payment, non-monetary psychological encouragement, fixed monetary incentive, performance based monetary incentive and lastly, a choice bonus (an option which offers a choice between the fixed incentive and the performance based monetary incentive). Each worker is randomly assigned to one of these ten experimental treatments. We evaluate the effect of our experimental treatments on our outcomes which we measure as 1) effort 2) productivity 3) data quality measures i.e., completeness, validity, and accuracy. Worker effort is measured as time taken by a worker to complete a task, worker productivity is measured as the speed or timeliness of a worker in completing a task; for data quality we measure completeness which quantifies how much of a task is completed by a worker, validity which calculates if the worker enters data which is considered valid or uses the appropriate format and accuracy measures the correctness of the task performed by a worker. We measure these effects using an ordinary least squares regression.

Firstly, we find that within the incomplete contractual setting, workers exert higher effort, across all treatments as compared to the baseline case of a fixed pay. Secondly, we find that only performance-based incentive mechanisms help improve data quality, as compared to other incentive mechanisms such as a non-monetary psychological encouragement, fixed monetary incentive, or choice-based incentive mechanisms (which

¹Once a worker performs a task on the online crowdsourcing platform and completes it, they submit it to an employer, who may then accept the completed task and pay the worker, or reject the completed task, and deny the worker his pay. For a more detailed context of this market design, please refer to section 2.

offer a choice between a performance-based incentive mechanism and a higher fixed wage). Further, we find that performance-based incentive mechanisms lead to improvement of contractable dimensions of data quality like completeness of tasks, however, they are unable to improve non contractable dimensions of data quality i.e., the validity and accuracy of the data collected. Further, we find that matching skills of workers to the task at hand can help improve data quality in terms of completeness of a task, it does not help improve the validity and accuracy of the data collected. We also see that while a worker is incentivized to complete the task with monetary incentives, this can lead to workers rushing through tasks which improves completeness at the cost of the validity and accuracy of the data.

Our research contributes to several streams of literature, especially the literature in gift-exchange. We find evidence that in an incomplete contract setting, both wage and effort levels are above the minimum legal requirements as hypothesized by the gift-exchange theory. The evidence for this hypothesis is mixed in the literature (Cassar and Meier, 2017; DellaVigna, and Pope, 2017; Difallah et al.,2014; List, and Momeni, 2017; Xia and Muthukrishnan, 2017). A study by, DellaVigna and Pope (2018) employed MTurk participants to determine whether economists are better than non-specialists in predicting the impact of different incentive levels on effort. Their treatment with a very low piece rate resulted in higher participation than no piece rate. The researchers found monetary incentives to be more effective than non-monetary psychological inducements to motivate workers Further, they found that expert economists failed to predict this result. Xia and Muthukrishnan (2017) match crowdworkers to their most preferred HITs; however, do not improve work quality; while Difallah et al. (2014) test for crowdworker retention across HITs. Another recent economic studies found that crowdworkers' performance quality declines when job requesters donate a portion of pay to charity (Cassar and Meier, 2017). Similarly, employee misbehavior was found to increase when businesses employ corporate social responsibility due to moral licensing (List and Momeni, 2017). Similar studies within traditional labor economics literature (which are not set in the incomplete contract context) also show interesting results evaluating the effect of monetary incentives on

worker performance. For example, Horton et al. (2011) investigate participants' acceptance choices when offered \$0.01, \$0.05, \$0.15, or \$0.25 to transcribe an extra paragraph. Although they do not include a control group receiving no incentives, they find that acceptance rates grow monotonically with higher piece rates. Similarly, Mason and Watts (2010) had participants classify traffic images and solve word puzzles with changing piece rates. When comparing no payment to a piece rate of one cent, however, they find that effort increases with higher piece rates without any exception to this rule, regardless of the work at hand or its degree of difficulty.

In our research we find that performance contingent financial incentives improve productivity of workers, while other incentive mechanisms we studied i.e., non-monetary psychological encouragements, fixed financial incentives and choice bonus, did not have the same effect. There is a large literature in economics on the relationship between financial compensation and productivity, however the evidence is inconsistent. There is a great deal of evidence to suggest that increasing the amount of performance-based financial incentives leads to an increase in productivity (Lazear 2000). However, some experimental economics literature suggests that such incentives did not have an effect on productivity or even caused it to decrease because low incentive pay can trigger "crowding out" intrinsic motivation (Gneezy and Rustichini, 2000). However, such results have not been seen in research done on online labor markets (DellaVigna and Pope, 2018). In general, real-effort trials carried out in online labor marketplaces such as Amazon's MTurk have, for the most part, been unable to uncover any detrimental impacts (on effort or productivity) from low piece rates. This is possibly due to the fact that majority of the activities undertaken cannot be categorized as being intrinsically motivating.

Further, studies have also explored the role that monetary compensation may have on data quality. In our study, we find that monetary incentives can help improve completeness of tasks, however, they do not help improve the validity and accuracy of the data collected. More specifically, within the monetary incentives we studied through our treatments, we find that performance-based incentives were more effective than the other monetary

incentives and gifts in improving volume of data collected, however, they did not affect the quality of data collected (i.e. accuracy and validity of data). We did not see similar effects of non-monetary psychological encouragements, fixed financial rewards, or choice bonus options on worker performance. Literature on the topic, shows that payment rates have almost no discernible impact on data quality across a wide range of tasks, including picture sorting and crossword puzzle completion (Mason and Watts, 2009), computer game performance (Horton and Chilton, 2010), survey studies (Buhrmester et al., 2011), and transcription (Marge, Banerjee, and Rudnicky, 2010). Mason and Watts (2009) and Rogstadius et al. (2011) found that as the magnitude of a fixed financial incentive improved, completeness of tasks improved, however, the work quality of tasks did not improve. Yin et al., 2013 found that magnitude of a performance contingent incentive did not affect the worker quality or effort. However, when tasks are done in sequence, an increase in incentive magnitude can improve worker effort and quality. Harris (2011) studied performance contingent financial incentives and showed that the quality of work was higher when having such incentives than when not having them.

We measure data quality using three metrics i.e., completeness, validity, and accuracy. While these data quality metrics have been measured in the past literature, the effect of monetary incentives on data quality, has primarily been measured using the completeness data quality measure and unambiguous tasks (Buhrmester et al., 2011; Horton and Chilton, 2010; Marge, Banerjee, and Rudnicky, 2010; Mason and Watts, 2009). Very limited literature has begun to understand the impact of monetary incentives on non-contractable dimensions (i.e. validity and accuracy) for tasks (Alonso and Baeza-Yates, 2011; Grady and Lease, 2010; Kazai et al., 2013; Shaw et al., 2011). The tasks used in this literature primarily rely on a worker providing a relevance label to a text.² While these tasks may include some subjective judgement on part of the worker, they are often in a standard format, and require lower effort and cognitive ability, unlike the ambiguous tasks we use in

²In this type of task, typically a worker is presented with a paragraph of a text and asked a multiple choice question of whether the text is relevant to a query that is presented.

our experiment. Grady and Lease (2010) looked at how changing different parts of the HIT design, such as the title, terminology, and pay, influenced the accuracy of the annotations, however, they did not have any conclusive results of effect of monetary incentives on accuracy of the annotations. Shaw et al. (2011) evaluated effects of social and financial incentive systems on annotation accuracy and found that outcomes depended on task complexity, while monetary incentives had no influence on accuracy. Kazai et al., 2013 conducted experiments where they vary the level of pay offered, the effort required to complete a task and the qualifications required of the workers, to see the effects on the accuracy of relevance labels provided by crowd source workers. They found that level of pay influences label accuracy, where higher pay produces more reliable labels, and lower pay increases the number of inaccurate labels and unreliable results.

Lastly, we find that while skill matching can improve productivity and task completeness, it does not improve effort, and non-contractable dimensions of data quality i.e., validity and accuracy. These results, especially regarding accuracy and validity, are counter intuitive, and do not align with previous literature (Bailey et al., 2008). Firstly, it is possible that as skill matching was self-reported (as energy experience of worker), it may have motivated employees to exaggerate their abilities. Secondly, it is possible that the self-reported replies might represent crowd workers' confidence and attitude. Kazai et al., 2013, find similar results, where workers with high familiarity of a subject showed low accuracy results. Further, they find, while this was true for unqualified workers (who do not pass their qualification criterion), this was not true for qualified workers (who pass their qualification criterion).

Our paper further enhances our knowledge about the effectiveness of monetary and non-monetary incentives on worker effort, productivity, and data quality within the incomplete contract context. On a more general level, our study is related to an increasing number of recent papers that study what motivates effort, productivity, and data quality in online labor markets and testing the gift exchange hypothesis (Cassar and Meier, 2017; DellaVigna, and Pope, 2017; Difallah et al., 2014; List, and Momeni, 2017; Xia and

Muthukrishnan, 2017). Most previous literature which tests the gift exchange hypothesis does this in a context where the contract is complete and the outcome is well defined, based on unambiguous tasks. Our contribution to this growing field is to study the online labor market and test the gift exchange hypothesis in a context where the contract is truly incomplete which has outcome work quality measures that are not contracted on. In our study we use both ambiguous and unambiguous task components which makes our study results and contributions novel.

3.2 Online labor markets

According to Katz and Krueger, 2016, flexible work arrangements accounted for 94 percent of the net employment growth in the U.S. economy between 2005 and 2015. According to the online labor index which measures the supply and demand of online freelance labor across countries and occupations, online labor markets have grown over 70 percent worldwide in the past 5 years. These markets are of growing importance, especially in a post covid world. Katz and Krueger define flexible work arrangements as involving “temporary help agency workers, on-call workers, contract workers, and independent contractors or freelancers”, which includes work done via digital labor markets such as Uber, TaskRabbit or MTurk to a large extent. Within the online labor markets, more specifically, online crowdsourcing platforms that are the focus of our study, allows workers to enter flexible, short-term agreements to provide on-demand. A dominant example is Mturk market for data entry, surveys, and Human Intelligence Tasks that provide training data for artificial intelligence programs. It is a crowdsourcing marketplace where a job requester can post tasks and find participants who want to complete those tasks – across the world. Employers who post the task control the contract design, including the wage rate, time allowed per task, how long the task may be available for workers to complete, and how many times they require a task to be completed.

Workers can examine tasks and contract terms before they choose to complete them. Worker personal identity is not disclosed to employers, and they can be identified by

employers only on the basis of a unique id which is a string of numbers and letters. Workers can accept a task after reviewing terms and start working on it. Once a task is submitted by a worker, an employer can accept a task or reject it. If the task is accepted, the worker gets paid, if not, the worker does not get paid.

The exchange between job requesters and crowdworkers can be described as a one shot game with the stages 1 to 4 as described.

(1) Requesters make a take it or leave it offer for crowdsource workers with high or low wages and task descriptions.

(2) Workers accept or reject the task.

(3) Workers perform the task at high or low quality.

(4) Requesters accept and pay or deny and not pay.

This market design has several problems. This structure of the online labor market gives significant bargaining power to the job requester, who controls wages (Dube et al., 2018). The environments offered by these current systems are not fair and workers can easily be exploited and are frequently grossly underpaid. The current platforms and environment do not cultivate trust in the workplace. This design does not reward high-quality performance, which can result in disgruntled workers if job requesters don't like the work and give it low ratings. Such an environment can lead to a low-trust, low-wage, low-data quality equilibrium (Gray and Suri, 2019). Further, this design does not match skills of workers to the tasks at hand (Berg et al., 2013). For example, Berg, 2015 finds that crowd workers have both high mean and variance education levels, indicating room for improvement in matching of task to ability.

3.3 Experiment Design

3.3.1 Hypothesis

Based on the gift-exchange theory we test the following hypothesis:

(1) Workers respond to high wage levels by increasing their effort, productivity, and data quality (positive reciprocity).

(2) Workers respond to non-monetary encouragements by increasing their effort, productivity, and data quality (positive reciprocity).

(3) A guarantee against task rejection by the employer increases worker effort, productivity, and data quality (positive reciprocity).

3.3.2 Treatments

To test these hypotheses, we use several treatments and controls. Our experimental framework had ten treatments– and the sample respondents were randomly evenly split across the treatments. This unconfounded worker assignment to treatment groups helped us randomly assign workers to the treatment groups which is a necessary condition for estimating causal effects and ensuring that our variables are exogeneous. Further, we also randomize the treatments for the workers. We ensured that workers were not changing groups once assigned a treatment group in two ways 1) the workers were unaware of the different treatment groups, and 2) the Amazon Mturk software tracked IP addresses of workers and prevented them from changing the treatment group once they were assigned the group. It is possible that a worker could have multiple user identities, and could access the task from multiple IPs, however Mturk has designed several policies and software features which prevent a worker from having more than a single account.

In the first phase of the experiment, the worker accepts or rejects the consent to perform a task. At this stage the worker is also told that they will be offered a minimum of \$2.75 for the task, while some tasks may receive a higher pay. A key concern of crowd source workers in the online crowdsourcing platforms is rejection of work after completion. Taking this into consideration, we have two framing treatments – one guarantees that complete work will be accepted and paid a baseline rate, while the other does not offer a task acceptance and pay guarantee. This framing treatment is interacted with five other payment treatments to develop a 2X5 experimental design to test the gift exchange hypothesis (Figure 3.1). These ten treatments are assigned randomly to workers using Survey Monkey.

The payment treatments are of five types³:

(1) Baseline: This offers a fixed pay and no gift. The payment is \$3.50 for completion of the data entry task (Baseline: N = 159; Baseline No Rejection: N = 163).

(2) Plea for accuracy: This treatment offers the same wage as the baseline treatment, \$3.50 flat fee for completion of data entry task. It also includes an explicit message in the task description about the importance of accurate data entries and appeals to the good will of the worker (Plea = 164; Plea – no rejection = 192).

(3) Up front bonus: Here, we offer a base pay of \$2.75 plus a \$0.75 up front bonus as an inducement to provide accurate data entries. Here, while the worker receives the same payment as in the baseline and plea treatment, they receive an explicit message that the task includes a guaranteed monetary bonus of \$0.75 that is an advance reward for providing accurate data (Upfront Bonus = 203; Upfront Bonus – no rejection = 181).

(4) Performance bonus: Here, we offer a base pay of \$2.75 plus a \$1.50 performance bonus after task completion if the work satisfies an accuracy threshold. The workers receive an additional \$1.5 if they give high quality answers and an additional \$0 if they do not give high quality answers. This monetary bonus is based on their performance (Conditional Bonus = 190; Conditional Bonus – no rejection = 163).

(5) Bonus choice: In the fifth payment treatment, the worker has more control of his payment environment and can choose between the upfront bonus or the performance bonus. He receives a wage of \$2.75 plus the worker chooses between the up-front bonus and the performance bonus before beginning. (Choose Bonus = 283; Choose Bonus – no rejection = 296).

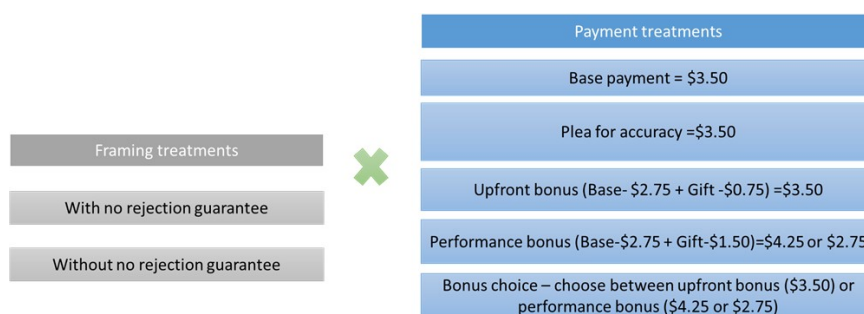
The baseline forms the control treatment group. A fixed monetary incentive (upfront bonus or treatment 3), performance based monetary incentive (performance bonus or treatment 4) and bonus choice (treatment 5) helps us test the second hypothesis using different compensation methods. Non-monetary psychological encouragements (treatment

³N provided for all the treatment types is for all workers who agreed to the payment assignment i.e., 1993 workers. Of these workers, 1071 completed the task, while the remaining 922 did not finish the task.

2) are used to test the first hypothesis. The framing treatment (no rejection guarantee) which is interacted with the five payment treatments is used to test the third hypothesis.

After being randomly assigned to a treatment group, the worker will accept or reject their payment terms and proceed to finish the task or exit from the experiment without finishing the task. Our sample includes all the respondents that agreed to the payment terms they were assigned. Respondents could be assigned to the control group i.e., the base pay or the other treatments as shown in Figure 3.1.

Figure 3.1: Experiment design



Notes: The figure represents the 2X5 experiment design with ten treatments. The two framing treatments are interacted with each of the five payment treatments to give us ten treatments that we used in the experiment.

3.3.3 Experimental setting

We recruited experimental workers using a crowdsourcing platform – Amazon Mturk to complete the research. In our experiment, we used the adult US population in large or medium-sized metropolitan areas as a sample. We posted the description of the task online on Mturk and hosted the task on an external website i.e., Survey Monkey that the workers could reach by using a link. When the workers completed the task, they received a completion code which they entered into the Mturk interface for completion. Over 1993 workers consented to participate, accepted the payment terms, and started the task, 1071 workers completed the task and received a payment, while 922 workers, left the task incomplete, and did not receive the payment.

The crowdsourced workers were asked to download a corporate sustainability report and complete a data entry task with the information found in the report. The survey they filled, included questions about renewable energy investments of a company for a given year. The corporate sustainability reports which were chosen for a survey were compiled by research assistants who gathered two key aspects of every report i.e., year for the sustainability report, and the company name. Over 200 CSR reports of companies for different years were selected at random and utilized for the experiment. Multiple workers had the opportunity to work on the same report, which gave us a chance to measure data quality variables for each report. Each worker was randomly assigned to a company report and to a payment treatment.

The workers had two types of tasks while filling these surveys, one was an ambiguous task, while the other was an unambiguous task. An example of an unambiguous task was that workers were asked to enter the name of the company and the year of the report,. This information is often available to the worker on the report cover and can be easily verified. Some examples of the ambiguous tasks where workers were asked to enter information which is 1) report specific and 2) project specific information. Report specific data included data on renewable energy goals of the company, the numerical value, and units of the goal of the company. Project specific data was gathered through questions on specific project level information for a company i.e., name of the project, type of renewable energy, the year the project is announced and completed, the total quantity and units per project, and project type. Some of these answers required a value to be put in a certain format, while some of these answers were multiple choice questions with drop down options. Examples of ambiguous tasks were part of the information provided in the report, which has a non-standard format. Each sustainability report is organized differently – there is no standard structure of these documents, and no two reports include exactly the same set of information for a given company in a given year. The non-uniform format of corporate sustainability reports makes this task ambiguous. This requires workers to use their cognitive ability, subjective judgement, and effort to fill out these ambiguous tasks.

Unambiguous tasks are therefore considered simple and not tedious to complete. On the other hand, ambiguous tasks are difficult, more time consuming, and needed more effort from workers for completion. Our goal is to analyze the gift exchange model on incomplete contracts, and in our case, ambiguous tasks make the contract truly incomplete, since the worker is asked to perform these tasks which are not explicitly specified in the project description, and thus workers do not have a written contract regarding the quality of these tasks.

3.3.4 Measuring outcome

We measure the outcome of the data entry task in three ways i.e., worker effort, worker productivity or speed and data quality. Further, data quality has three components i.e. completeness, validity, and accuracy, as commonly used in the computer science literature. These variables were calculated using different approaches to check for robustness. These calculations are described in more detail in Section 5, while discussing the results.

(1) Worker effort – We calculate a measure for worker effort using the time spent by the worker on the complete task ⁴.

(2) Worker productivity or speed - This measure was calculated by the number of fields filled per second.

(3) Data quality is measured as completeness, validity and accuracy:

(a) Completeness – This measure calculates how much of the various data entry tasks were completed. This was measured by checking how many fields were filled by a worker and if the worker finished the task or not.

(b) Validity – This measure calculates how many of the data fields were entered with the correct formatting (e.g., if a year was requested, did the worker enter a four-digit number within the relevant range of possible years, did the worker enter a number between 1 to 100 when they were requested to enter a percentage etc.).

⁴This was asked using the question: “Was there any additional information on renewable energy projects in the report that you think may be useful for us? Please use this space to add any additional information from the report.” Since these questions were asked at the end of the survey, and are open ended, we use this as a measure of how much effort a worker may have put into finishing the survey.

(c)Accuracy – This measure calculates how many of the data fields contained correct information from the data entry task.

3.4 Empirical approach

We measure the effect of different incentive structures on the outcomes (worker effort, productivity and data quality) through an ordinary least squares equation as shown in Equation 3.1. Here worker data quality is the dependent variable, and the worker incentive and gift treatments form the explanatory variables. We use several self-reported controls in the equations. These include worker experience in the energy field, worker mood, worker reported productivity, air quality rating, worker confidence in topic, and worker employment part time or full time outside of MTurk. These controls are self-reported and defined in our experiment as:

(1) Energy experience: This variable provides a score between 1 to 7 rating the familiarity a worker has with the energy industry, with 1 being completely unfamiliar and 7 being very familiar.

(2) Mood: This variable provides a score between 1 to 7 of the workers mood when completing the task, with 1 being much worse than average and 7 being much better than average.

(3) Reported productivity ⁵: This variable provides a score between 1 to 7 of the workers productivity when completing the task, with 1 being much lower than average and 7 being much higher than average.

(4) Air quality: This variable provides a score between 1 to 7 of the workers rating of the air quality when completing the task, with 1 being very poor and 7 being very high.

(5) Confidence: The worker is asked to report this variable at the end of the task, where they are asked to rate their confidence in the accuracy of the data they report on a scale of 1 to 7, with 1 being very low and 7 being very high.

(6) Employment: The worker is asked to report this variable at the end of the task,

⁵This control variable is reported productivity and is self-reported by the worker. One of our outcome variables is productivity, which is measured in the experiment as the speed or timeliness with which a worker completes a task (how many fields does a worker fill in a given amount of time?).

where they are asked whether they are currently employed in part-time or full-time work outside of MTurk.

$$Q_w = \alpha + \beta Q_w + \gamma X_w + \varepsilon_w \tag{3.1}$$

$Q_w = \textit{Worker data quality outcome}$

$I_w = \textit{Worker incentive}$

$X_w = \textit{Worker control variable}$

3.5 Results and discussions

We first present the results from our framing treatments, then the payment treatments, and then the 2X5 treatment design. Using the 2X5 treatment design we present results for the sample of workers who finished the task, and then present robustness checks using the full sample (workers who finished and those who did not finish the tasks). Next, we extend our analysis to include other outcomes which may be of interest. We also check the robustness of the findings for the data quality measures of accuracy and validity, by controlling for completeness of the survey. The summary statistics are provided in Appendix B.

3.5.1 Main results

Table 3.1 shows us the final experiment results which checks the effect of our framing treatment, i.e., the rejection guarantee on our outcome measures. We see that by providing the workers an option of a no rejection of their work guarantee, does not improve worker productivity or data quality, while it does improve effort for workers who finished the tasks. Thus, while the no-rejection guarantee improves effort applied by workers, it does not improve data quality or worker productivity.

This finding partially confirms our hypothesis that a guarantee against task rejection increases worker effort, productivity and quality. Rejection of work on MTurk costs the worker money, effort, and project ownership, and lowers their approval rating, making it harder to get future work. Unfair rejections may happen for a variety of reasons, including

Table 3.1: Final results with a dummy variable for the no reject guarantee

	<i>OLS</i> Filled	<i>OLS</i> Finished	<i>OLS</i> Accuracy	<i>OLS</i> Validity	<i>OLS</i> Speed	<i>OLS</i> Effort
	(1)	(2)	(3)	(4)	(5)	(6)
No rejection	-0.03 (0.06)	0.03 (0.02)	0.08 (0.05)	-0.02 (0.06)	0.001 (0.002)	632.46* (384.13)
Energy experience	0.24*** (0.02)	0.04*** (0.01)	-0.08*** (0.02)	0.25*** (0.02)	0.01*** (0.001)	-196.26 (150.55)
Confidence	-0.01 (0.02)		-0.01 (0.02)	-0.01 (0.02)	-0.001* (0.001)	260.79* (150.96)
Employment	0.24** (0.09)		-0.11 (0.08)	0.27*** (0.10)	0.01** (0.003)	475.98 (597.52)
Constant	-0.41** (0.20)	0.45*** (0.06)	0.21 (0.16)	-0.61*** (0.20)	0.03*** (0.01)	27.14 (1,231.07)
Observations	1,060	1,993	1,060	1,060	1,060	1,060
Adjusted R ²	0.11	0.01	0.02	0.11	0.06	0.002

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows the impact of a no reject guarantee dummy variable on our outcome variables i.e., data completeness, accuracy, validity, speed, and effort. We control for mood, productivity, air quality, energy experience, employment, and confidence in results as reported by the workers. Columns 1, 3, 4, 5, 6 consider only workers who finished the task (N = 1060), whereas column 2 considers all workers, some of whom did not finish the task (N=1993). We did not control for employment and confidence in column 2 for the finished variable.

but not limited to: poor job design, unclear instructions, technology issues, and malicious requesters, and can lead to loss of worker trust. Thus, removing this element of risk by guaranteeing task acceptance and payment helps to increase worker effort. Similarly, McInnis et al., 2016, find that reducing risks and building trust can improve outcomes for all parties in online labor markets.

Table 3.2 shows us the effect of just the five payment treatments (while not including an interaction with the rejection guarantee). It shows that only an upfront bonus improves completeness, while a performance-based incentive improves two data quality dimensions i.e., completeness of data and validity of data. We do not see any improvements of effort in this specification. Parsing these out further, Table 3.3 shows results of the effect of the 5

Table 3.2: Final results with payment treatments without the rejection guarantee

	<i>OLS</i> Filled z score	<i>OLS</i> Finished	<i>OLS</i> Accuracy	<i>OLS</i> Validity	<i>OLS</i> Speed	<i>OLS</i> Effort
	(1)	(2)	(3)	(4)	(5)	(6)
Plea	0.04 (0.10)	-0.004 (0.04)	-0.01 (0.09)	-0.01 (0.11)	-0.0001 (0.003)	-70.58 (656.90)
Upfront bonus	0.19* (0.10)	-0.0005 (0.04)	-0.05 (0.08)	0.15 (0.11)	0.001 (0.003)	-25.46 (646.81)
Performance incentive	0.25** (0.11)	-0.03 (0.04)	-0.06 (0.09)	0.23** (0.11)	0.003 (0.003)	-414.64 (667.80)
Bonus choice	0.06 (0.09)	0.02 (0.03)	0.12 (0.08)	0.03 (0.10)	-0.001 (0.003)	8.00 (592.39)
Energy experience	0.24*** (0.02)	0.04*** (0.01)	-0.07*** (0.02)	0.25*** (0.02)	0.01*** (0.001)	-182.46 (151.30)
Confidence	-0.01 (0.02)		-0.01 (0.02)	-0.01 (0.02)	-0.001* (0.001)	251.71* (151.26)
Employment	0.25*** (0.09)		-0.12 (0.08)	0.27*** (0.10)	0.01** (0.003)	478.88 (600.15)
Constant	-0.51** (0.20)	0.46*** (0.07)	0.23 (0.17)	-0.68*** (0.21)	0.03*** (0.01)	427.80 (1,293.53)
Observations	1,060	1,993	1,060	1,060	1,060	1,060
Adjusted R ²	0.12	0.01	0.02	0.12	0.06	-0.003

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows the impact of all the payment treatments without considering the no rejection guarantee e on our outcome variables i.e., data completeness, accuracy, validity, speed, and effort. We control for mood, productivity, air quality, energy experience, employment, and confidence in results as reported by the workers. Columns 1, 3, 4, 5, 6 consider only workers who finished the task (N = 1060), whereas column 2 considers all workers, some of whom did not finish the task (N=1993). We did not control for employment and confidence in column 2 for the finish variable.

Table 3.3: Final results of all payment treatments interacted with the no rejection guarantee

	<i>OLS</i> Filled (1)	<i>OLS</i> Finished (2)	<i>OLS</i> Accuracy (3)	<i>OLS</i> Validity (4)	<i>OLS</i> Speed (5)	<i>OLS</i> Effort (6)
Baseline - no rejection	-0.05 (0.15)	0.04 (0.06)	-0.05 (0.12)	-0.09 (0.15)	0.003 (0.004)	4,835.58*** (929.27)
Plea	0.14 (0.15)	0.01 (0.06)	-0.17 (0.12)	0.05 (0.16)	0.01 (0.005)	2,084.48** (949.88)
Plea - no rejection	-0.10 (0.15)	0.03 (0.05)	0.08 (0.12)	-0.15 (0.15)	-0.002 (0.004)	2,779.39*** (908.62)
Upfront bonus	0.12 (0.14)	0.02 (0.05)	-0.12 (0.12)	0.04 (0.15)	0.01 (0.004)	2,452.62*** (905.24)
Upfront bonus -no rejection	0.20 (0.15)	0.02 (0.05)	-0.04 (0.12)	0.18 (0.15)	0.0001 (0.004)	2,553.92*** (921.23)
Performance incentive	0.23 (0.15)	-0.05 (0.05)	-0.09 (0.12)	0.17 (0.16)	0.001 (0.004)	2,151.09** (946.73)
Performance incentive - no rejection	0.22 (0.15)	0.05 (0.06)	-0.08 (0.12)	0.19 (0.15)	0.01* (0.004)	2,074.52** (936.69)
Bonus choice	0.02 (0.13)	0.03 (0.05)	0.05 (0.11)	-0.03 (0.14)	-0.003 (0.004)	3,052.37*** (840.14)
Bonus choice- no rejection	0.04 (0.13)	0.04 (0.05)	0.14 (0.11)	-0.01 (0.14)	0.005 (0.004)	2,034.18** (831.07)
Energy experience	0.24*** (0.02)	0.04*** (0.01)	-0.07*** (0.02)	0.25*** (0.02)	0.01*** (0.001)	-186.25 (150.07)
Confidence	-0.01 (0.02)		-0.01 (0.02)	-0.01 (0.02)	-0.001* (0.001)	294.11* (150.06)
Employment	0.25*** (0.10)		-0.12 (0.08)	0.27*** (0.10)	0.01** (0.003)	493.23 (593.51)
Constant	-0.48** (0.22)	0.44*** (0.07)	0.26 (0.18)	-0.63*** (0.23)	0.03*** (0.01)	-2,337.00* (1,381.35)
Observations	1,060	1,993	1,060	1,060	1,060	1,060
Adjusted R ²	0.12	0.01	0.02	0.12	0.06	0.02

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows the impact of all the payment treatments interacted with the rejection guarantee on our outcome variables i.e., data completeness, accuracy, validity, speed, and effort. We control for mood, productivity, air quality, energy experience, employment, and confidence in results as reported by the workers. Columns 1, 3, 4, 5, 6 consider only workers who finished the task (N = 1060), whereas column 2 considers all workers, some of whom did not finish the task (N=1993). We did not control for employment and confidence in column 2 for the finish variable.

payment treatments interacted with the framing treatment (2X5 experimental design). From the results in Table 3.2 we see that workers are taking more time to finish tasks i.e., worker effort (column 1) improves when offered monetary or non-monetary incentives. and Worker productivity (column 5), improves when offered monetary incentives, particularly performance-based incentives. However, we don't see any significant effects of these incentives on the completeness of the task (Column 1), or if the task is finished or not (column 2). We also did not find evidence that incentives improved data quality in terms of the validity of data (column 3) or the accuracy of data (column 4).

3.5.2 Robustness check

In Table 3.4 we provide a robustness check which presents results for all the payment and framing treatments for the full sample, which includes workers who did not finish the task ⁶. When we compare the full sample results in Table 3.4 to the finished sample (sample of workers who finished the task) results in Table 3.3 we see different results for our effort, completeness, and validity variables, and the similar results for the speed and accuracy variable. Firstly, in our full sample results in Table 3.4 where we control for mood, reported productivity ⁷, energy experience of a worker, and their air quality, while not controlling for their confidence levels and employment, we see that completeness (fill) and validity of the data increases significantly when a worker is offered an incentive i.e. a performance bonus with no rejection. Whereas in the sample for workers who finished the tasks in Table 3.2, the completeness and validity data quality variables, did not significantly change with any incentive or gift exchange. Secondly, while both gift exchange and incentives do not improve our accuracy measure in the full and finished sample results, we see that, having higher energy experience helps improve accuracy significantly in the full results, whereas it negatively effects accuracy in the finished sample results. Thirdly,

⁶We do not control for worker employment and confidence which are self-reported by workers. Please refer to Section 4 for more details. These two questions appear at the end of the survey, and the workers that do not finish the task did not answer these two questions, hence, we were unable to include these controls in the full sample results.

⁷This refers to reported worker productivity, which is self-reported and a control variable, not the outcome variable productivity which is measured as the speed or timeliness with which a worker finishes a task.

Table 3.4: Robustness check - full sample results

	<i>OLS</i> Filled (1)	<i>OLS</i> Finished (2)	<i>OLS</i> Accuracy (3)	<i>OLS</i> Validity (4)	<i>OLS</i> Speed (5)	<i>OLS</i> Effort (6)
Baseline - no rejection	0.03 (0.11)	0.05 (0.06)	-0.02 (0.12)	0.0002 (0.11)	0.002 (0.003)	2,778.70*** (828.82)
Plea	0.11 (0.11)	0.02 (0.06)	-0.13 (0.12)	0.06 (0.11)	0.003 (0.003)	1,160.91 (838.72)
Plea - no rejection	-0.01 (0.10)	0.03 (0.05)	0.01 (0.12)	-0.02 (0.10)	-0.001 (0.003)	1,427.70* (802.93)
Upfront bonus	0.12 (0.10)	0.02 (0.05)	-0.06 (0.12)	0.08 (0.10)	0.003 (0.003)	2,191.32*** (793.93)
Upfront bonus -no rejection	0.13 (0.10)	0.02 (0.06)	0.001 (0.12)	0.11 (0.10)	0.0003 (0.003)	1,400.63* (811.73)
Performance incentive	0.08 (0.10)	-0.07 (0.05)	-0.07 (0.12)	0.06 (0.10)	-0.0002 (0.003)	1,009.51 (804.21)
Performance incentive - no rejection	0.24** (0.11)	0.06 (0.06)	0.001 (0.12)	0.22** (0.11)	0.01* (0.003)	1,103.33 (839.11)
Bonus choice	0.02 (0.09)	0.02 (0.05)	-0.03 (0.11)	0.002 (0.09)	-0.002 (0.003)	2,312.02*** (738.75)
Bonus choice- no rejection	0.10 (0.09)	0.04 (0.05)	0.05 (0.11)	0.08 (0.09)	0.004 (0.003)	1,272.95* (736.50)
Energy experience	0.20*** (0.02)	0.05*** (0.01)	0.05*** (0.02)	0.20*** (0.02)	0.004*** (0.0004)	78.53 (123.41)
Constant	-0.59*** (0.14)	0.45*** (0.08)	-0.23 (0.16)	-0.65*** (0.14)	0.02*** (0.004)	-2,475.51** (1,109.27)
Observations	1,816	1,816	1,816	1,816	1,816	1,816
Adjusted R ²	0.10	0.03	0.003	0.09	0.05	0.01

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows the impact of all the payment treatments interacted with the rejection guarantee on our outcome variables i.e., data completeness, accuracy, validity, speed, and effort. We control for mood, productivity, air quality and energy experience as reported by the workers. All the columns consider workers, both, who finished their tasks, and those who did not finish their tasks (N=1816).

we see that performance-based incentives have no effect on effort in the full sample, while they do show these effects on the finished sample. The main difference between results in the full sample results include workers who did not complete the task. To examine this further, we control for workers who finished their tasks on the full sample in Table 3.5, and we see that these effects reduce and lose significance, i.e., firstly, we see that validity improves with incentives, but is weakly significant. Secondly, we also see that the on the full sample the completeness variable while controlling for the finished results has a slightly lower magnitude i.e., 19 percent versus 24 percent, however, has improved significance. Thirdly, the accuracy variable, does not show any improvements with energy experience of the worker.

To explore the different data quality variables further, we evaluated different extensions of the variable we calculated in our main specification i.e., for completeness, validity, and accuracy, in Table 7, Table 8, and Table 9. Table 3.6 calculates completeness using two approaches 1) we checked for how many fields which described report specific data were filled and 2) we checked for how many fields which described project specific features were filled. Thus, we had completeness measures, which were calculated based on general report survey questions and project specific survey questions. In Table 3.6, the first column calculates the percentage deviation from the mean for report relevant fields which are filled, the second variable calculates the z score for report relevant fields which are filled (this variable is used in as the main completeness measure), the third variable calculates the percentage deviation from the mean for project specific fields, and the fourth variable calculates the z score for project relevant fields filled. Using the percentage deviation from the mean as a measure, completeness is positively impacted by incentives. This is true for the case of report relevant fields and project relevant fields. Based on our full sample results from Table 3.4 and Table 3.5, and these results from Table 3.6, we see consistently positive effects of performance based incentives on completeness of data, and estimate these effects at ~ 19 percent (Table 3.5) based on the full sample.

Table 3.7 calculates validity which is a count of the data fields which were entered with

Table 3.5: Full sample results while controlling for workers who finished their tasks

	<i>OLS</i> Filled (1)	<i>OLS</i> Finished (2)	<i>OLS</i> Accuracy (3)	<i>OLS</i> Validity (4)	<i>OLS</i> Speed (5)	<i>OLS</i> Effort (6)
Baseline - no rejection	-0.01 (0.09)	0.05 (0.06)	-0.05 (0.12)	-0.04 (0.10)	0.002 (0.003)	2,763.95*** (828.99)
Plea	0.09 (0.09)	0.02 (0.06)	-0.14 (0.12)	0.05 (0.10)	0.003 (0.003)	1,154.86 (838.77)
Plea - no rejection	-0.04 (0.09)	0.03 (0.05)	-0.01 (0.11)	-0.05 (0.09)	-0.001 (0.003)	1,416.28* (803.05)
Upfront bonus	0.10 (0.09)	0.02 (0.05)	-0.07 (0.11)	0.06 (0.09)	0.003 (0.003)	2,184.90*** (793.98)
Upfront bonus -no rejection	0.11 (0.09)	0.02 (0.06)	-0.01 (0.11)	0.10 (0.09)	0.0000 (0.003)	1,394.71* (811.78)
Performance incentive	0.13 (0.09)	-0.07 (0.05)	-0.03 (0.11)	0.11 (0.09)	0.001 (0.003)	1,030.86 (804.55)
Performance incentive - no rejection	0.19** (0.09)	0.06 (0.06)	-0.03 (0.12)	0.17* (0.10)	0.004 (0.003)	1,083.08 (839.41)
Bonus choice	0.003 (0.08)	0.02 (0.05)	-0.04 (0.10)	-0.01 (0.09)	-0.003 (0.002)	2,305.90*** (738.80)
Bonus choice- no rejection	0.06 (0.08)	0.04 (0.05)	0.03 (0.10)	0.04 (0.09)	0.003 (0.002)	1,258.59* (736.68)
Energy experience	0.15*** (0.01)	0.05*** (0.01)	0.02 (0.02)	0.16*** (0.01)	0.003*** (0.0004)	60.68 (124.84)
Finished	0.87*** (0.04)		0.56*** (0.05)	0.80*** (0.04)	0.02*** (0.001)	326.77 (345.07)
Constant	-0.99*** (0.13)	0.45*** (0.08)	-0.48*** (0.16)	-1.01*** (0.13)	0.02*** (0.004)	-2,623.16** (1,120.20)
Observations	1,816	1,816	1,816	1,816	1,816	1,816
Adjusted R ²	0.30	0.03	0.07	0.26	0.13	0.01

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows the impact of all the payment treatments interacted with the rejection guarantee on our outcome variables i.e., data completeness, accuracy, validity, speed, and effort. We control for mood, productivity, air quality and energy experience as reported by the workers. Additionally, we also control for workers who finished their tasks. All the columns consider workers, both, who finished their tasks, and those who did not finish their tasks (N=1816).

Table 3.6: Completeness

	<i>OLS</i> Pct deviation from mean	<i>OLS</i> Filled	<i>OLS</i> Pct deviation from mean-by project	<i>OLS</i> Z score - by project
	(1)	(2)	(3)	(4)
Baseline - no rejection	-0.03 (0.11)	-0.05 (0.15)	-0.07 (0.16)	-0.06 (0.15)
Plea	0.08 (0.11)	0.14 (0.15)	0.09 (0.16)	0.14 (0.16)
Plea - no rejection	-0.03 (0.11)	-0.10 (0.15)	-0.06 (0.15)	-0.12 (0.15)
Upfront bonus	0.13 (0.11)	0.12 (0.14)	0.15 (0.15)	0.11 (0.15)
Upfront bonus -no rejection	0.16 (0.11)	0.20 (0.15)	0.22 (0.16)	0.21 (0.15)
Performance incentive	0.20* (0.11)	0.23 (0.15)	0.25 (0.16)	0.22 (0.16)
Performance incentive - no rejection	0.23** (0.11)	0.22 (0.15)	0.31* (0.16)	0.22 (0.15)
Bonus choice	0.05 (0.10)	0.02 (0.13)	0.07 (0.14)	0.01 (0.14)
Bonus choice- no rejection	0.09 (0.10)	0.04 (0.13)	0.11 (0.14)	0.03 (0.14)
Energy experience	0.19*** (0.02)	0.24*** (0.02)	0.25*** (0.03)	0.24*** (0.02)
Constant	-0.63*** (0.17)	-0.48** (0.22)	-0.96*** (0.23)	-0.47** (0.23)
Observations	1,060	1,060	1,060	1,060
Adjusted R ²	0.12	0.12	0.11	0.11

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows the impact of all the payment treatments interacted with the rejection guarantee on the completeness variables computed. We control for mood, productivity, air quality, energy experience, employment, and confidence in results as reported by the workers. All columns consider who finish the task (N=1060).

Table 3.7: Validity

	<i>OLS</i> Pct deviation from mean (1)	<i>OLS</i> Validity (2)	<i>OLS</i> Z score by respondent (3)
Baseline - no rejection	-0.08 (0.15)	-0.09 (0.15)	-0.19 (0.14)
Plea	0.08 (0.16)	0.05 (0.16)	-0.08 (0.14)
Plea - no rejection	-0.13 (0.15)	-0.15 (0.15)	-0.24* (0.14)
Upfront bonus	0.08 (0.15)	0.04 (0.15)	-0.12 (0.14)
Upfront bonus -no rejection	0.19 (0.15)	0.18 (0.15)	-0.14 (0.14)
Performance incentive	0.26* (0.16)	0.17 (0.16)	-0.31** (0.14)
Performance incentive - no rejection	0.25 (0.16)	0.19 (0.15)	-0.17 (0.14)
Bonus choice	-0.02 (0.14)	-0.03 (0.14)	-0.24* (0.13)
Bonus choice- no rejection	0.003 (0.14)	-0.01 (0.14)	-0.28** (0.12)
Energy experience	0.26*** (0.02)	0.25*** (0.02)	-0.10*** (0.02)
Constant	-0.74*** (0.23)	-0.63*** (0.23)	0.32 (0.21)
Observations	1,060	1,060	1,060
Adjusted R ²	0.13	0.12	0.02

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows the impact of all the payment treatments interacted with the rejection guarantee on the validity variables computed. We control for mood, productivity, air quality, energy experience, employment, and confidence in results as reported by the workers. All columns consider who finish the task (N=1060).

Table 3.8: Accuracy

	<i>OLS</i> Pct deviation from mean	<i>OLS</i> Accuracy	<i>OLS</i> Z score by respondent reporting	<i>OLS</i> Year reporting	<i>Poisson</i> Levenshien score
	(1)	(2)	(3)	(4)	(5)
Baseline - no rejection	-0.05 (0.04)	-0.05 (0.12)	-0.05 (0.13)	0.004 (0.06)	-0.11 (0.21)
Plea	-0.07 (0.05)	-0.17 (0.12)	-0.15 (0.13)	-0.06 (0.07)	-0.21 (0.22)
Plea - no rejection	0.01 (0.04)	0.08 (0.12)	0.12 (0.13)	0.03 (0.06)	-0.15 (0.20)
Upfront bonus	-0.08* (0.04)	-0.12 (0.12)	-0.16 (0.13)	-0.02 (0.06)	-0.22 (0.20)
Upfront bonus -no rejection	-0.04 (0.04)	-0.04 (0.12)	-0.13 (0.13)	-0.02 (0.06)	-0.18 (0.21)
Performance incentive	-0.06 (0.05)	-0.09 (0.12)	-0.22 (0.13)	-0.02 (0.07)	-0.13 (0.21)
Performance incentive - no rejection	-0.04 (0.04)	-0.08 (0.12)	-0.13 (0.13)	0.05 (0.06)	0.04 (0.20)
Bonus choice	0.01 (0.04)	0.05 (0.11)	-0.04 (0.12)	0.04 (0.06)	-0.02 (0.18)
Bonus choice- no rejection	0.04 (0.04)	0.14 (0.11)	0.05 (0.12)	0.04 (0.06)	-0.05 (0.18)
Energy experience	-0.03*** (0.01)	-0.07*** (0.02)	-0.16*** (0.02)	-0.11*** (0.01)	-0.17*** (0.03)
Constant	0.13* (0.07)	0.26 (0.18)	0.31 (0.19)	1.13*** (0.10)	0.04 (0.30)
Observations	1,060	1,060	1,060	1,060	1,060
Adjusted R ²	0.03	0.02	0.07	0.12	

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows the impact of all the payment treatments interacted with the rejection guarantee on the validity variables computed. We control for mood, productivity, air quality, energy experience, employment, and confidence in results as reported by the workers. All columns consider who finish the task (N=1060).

the correct formatting. The first column in table is percent deviation from the mean validity for a report, the z-score of the mean validity of a report (this variable is used as the main validity measure), and z score for the relative validity for a report i.e., the validity relative to the number of fields attempted by a person. We see that the pure deviations from average validity (which have a measure of completeness baked in) are positive in response to a performance-based incentive, but the effect on the relative measure of validity is weakly negative for some monetary incentives and gifts. The relative validity measure is also negatively correlated with energy experience. This suggests that workers may be potentially rushing through a lot of tasks and completing many tasks while giving invalid answers. To examine this further, for workers who finished their tasks, we evaluate the validity measure while controlling for completeness of the task (Table 3.9) and see that our validity measure shows a negative effect of various incentives and gifts. Thus, we can see that data validity does not improve with incentives and gifts, perhaps, there is a weakly negative significant effect of incentives and gifts (particularly fixed monetary incentives and non-monetary encouragements) on validity of data for workers who finish the task. Table 3.8 calculates accuracy using three approaches: 1) by checking the year of the report, 2) by using the Levenstien distance to measure the accuracy of the reported company name on the report, and 3) through an accuracy measure which we developed for the ambiguous tasks. For the first, we check if the year entered by the worker is within one year of the accurate value of the year which was earlier recorded by research assistants for every report that was used in the survey. A one-year margin was provided since CSR reports often cover a financial year, thereby labeling two calendar years (for e.g. reports are often labeled for the financial year i.e. 2016 – 17), in which case a worker could enter either year. For the second accuracy measure, we measure the accuracy with which a worker enters the name of the company for which they download the report, by checking the minimum number of “edits” that would be required to transform the company name they provided, to the accurate company name which was recorded by research assistants for a given report. This minimum-number-of-edits metric is called the edit distance, or the Levenshtein distance.

Table 3.9: Validity, accuracy and effort with a completeness control

	<i>OLS</i> Accuracy	<i>OLS</i> Validity	<i>OLS</i> Effort
	(1)	(2)	(3)
Baseline - no rejection	-0.07 (0.11)	-0.04 (0.04)	4,835.64*** (929.76)
Plea	-0.12 (0.11)	-0.09** (0.04)	2,084.30** (950.72)
Plea - no rejection	0.05 (0.11)	-0.06 (0.04)	2,779.52*** (909.25)
Upfront bonus	-0.08 (0.11)	-0.09** (0.04)	2,452.47*** (905.98)
Upfront bonus -no rejection	0.03 (0.11)	-0.02 (0.04)	2,553.67*** (922.48)
Performance incentive	-0.01 (0.11)	-0.05 (0.04)	2,150.81** (948.21)
Performance incentive - no rejection	-0.01 (0.11)	-0.03 (0.04)	2,074.24** (938.12)
Bonus choice	0.06 (0.10)	-0.04 (0.04)	3,052.35*** (840.54)
Bonus choice- no rejection	0.16 (0.10)	-0.05 (0.04)	2,034.12** (831.51)
Energy experience	0.003 (0.02)	0.01 (0.01)	-186.55 (157.28)
Confidence	-0.01 (0.02)	-0.003 (0.01)	294.12* (150.14)
Employment	-0.04 (0.07)	0.03 (0.03)	492.91 (595.74)
Filled z score	-0.32*** (0.02)	0.99*** (0.01)	1.26 (193.39)
Constant	0.11 (0.17)	-0.15** (0.06)	-2,336.39* (1,385.19)
Observations	1,060	1,060	1,060
Adjusted R ²	0.17	0.94	0.02

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows the impact of all the payment treatments interacted with the rejection guarantee on the accuracy, validity and effort variables computed. We control for mood, productivity, air quality, energy experience, employment, and confidence in results as reported by the workers, and we also control for completeness. All columns consider workers who finish the task (N=1060).

For the third accuracy measure, we rely on the fact that multiple workers complete the same survey questions about the same report, and to check for accuracy, we compare the modal answers for a question on a specific report, and the modal answers are flagged as accurate, and workers answers are checked for accuracy against these modal answers. If no modal answer was found for a field (every worker gave different answers for the field for that report), then the modal answer was marked as missing. In this case, the accuracy measure would have fewer fields for which accuracy could be measured for a given report. We calculated accuracy of all general report fields for every worker.

In Table 3.8, the columns calculates percent deviation from the mean accuracy for a report, the z-score of the mean accuracy of a report (this variable is used in as the main accuracy measure), z score for the relative accuracy for a report i.e., the accuracy relative to the number of fields attempted by a person, checking the accuracy of the reported year, and Levenshtein distance to measure accuracy of the reported company name. We see that all the approaches used to measure accuracy led to the same conclusion that, accuracy of data quality does not improve with incentives or gifts significantly. To examine this further, for workers who finished their tasks, we evaluate the accuracy measure while controlling for completeness of the task (Table 3.9) and see that our accuracy measure does not show any significant changes with incentives and gifts. Our non-significant results for accuracy show consistency across the sample of finished workers and the full sample.

Summarizing, after checking our main results for robustness we have the following findings: 1) Worker effort improves with monetary incentives and gifts (Table 3.3 and Table 3.9) for all the sample of workers who finish the tasks. Additionally, we see that for the full sample, performance based incentives do not show an increase in effort (Table 3.4 and Table 3.5). This is possibly because some workers are not motivated enough by the performance-based incentive and drop out before finishing the task. 2) We also see consistently positive effects of performance-based incentives on worker productivity or speed of task (~ 1 percent) performed in our results (i.e., Table 3.3 and Table 3.4). 3) Contractable dimensions of data quality i.e., completeness of data improves with monetary

incentives particularly, performance-based incentives for the sample of workers who finish their tasks (~ 23 percent). 4) We do not see any effects of monetary and non-monetary incentives on non-contractable dimensions of data quality i.e., validity and accuracy of data (Table 3.9). Incentives and gifts (especially fixed monetary incentives and non-monetary encouragements) may have a slightly negative significant influence on the validity of data for workers who complete the task (Table 3.9). 5) We also see that matching skills of workers to the task at hand does not impact accuracy or validity of data quality (Table 3.9), while it improves completeness of tasks (~ 24 percent), and worker productivity (~ 1 percent) consistently in our results (Table 3.3).

3.6 Conclusions

In this research we tested the gift-exchange hypothesis to understand how monetary and non-monetary incentives effect worker effort, productivity and data quality. Within data quality we examined contractable dimensions (completeness) and non-contractable dimensions (i.e., accuracy and validity). The MTurk workers were asked to complete a task which had ambiguous and non-ambiguous parts, and due to the presence of these ambiguous parts, we were able to measure non-contractable dimensions of data quality and perform skill matching based on self-reported data.

These results show that monetary incentives, particularly performance contingent incentives, may lead to improvements seen in worker effort, productivity and contractable dimensions of data quality (completeness). However, these performance contingent monetary incentives do not lead to improvements in non-contractable dimensions of data quality (i.e. validity and accuracy). In our results we also observe that skill matching helped to improve worker productivity and contractable dimensions of data quality (completeness) outcomes, but not the non-contractable dimensions of data quality (i.e., validity and accuracy). These findings agree with literature which has found limited impacts of incentives and gifts on data quality (Buhrmester et al., 2011; Horton and Chilton, 2010; Marge et al., 2010; Mason and Watts, 2009). Our main contribution to this

growing literature on gift exchange and online labor markets is to test the gift exchange hypothesis in a context where the contract is truly incomplete.

While the research study examined potential factors which influence worker effort, productivity and data quality in an incomplete contract setting in online labor markets, we did not examine this in a setting where there are repeated interactions of the employer and worker, and this can be a potential future research topic. Further, understanding how employment relations evolve with respect to worker performance and pay in incomplete contractual relationships, especially in a context where expectations may not be met. According to Fehr et al. (2011) even when contracts are incomplete, they help set subjective expectations and act as reference points for performance not specified in the contract. Costs of completing tasks are revealed after initial contracting, and workers can become aggrieved if conditions deviate from expectations.

CHAPTER 4

IMPACTS OF DISTRIBUTED SOLAR ON DISTRIBUTION GRID RELIABILITY

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4.1 Introduction

Renewable energy is fueling an energy transition in the U.S. as states race to address climate change concerns and reach their carbon emission goals. This transition has led to active debates in communities to understand the most economically efficient ways to implement renewable energy resources. Distributed solar photovoltaic (PV) systems have been widely deployed across the United States in recent years. In 2021, the U.S installed a record of 23.6 gigawatt (GW) of solar capacity, an increase of over 19 percent over 2020, and distributed solar made up almost one third of this capacity (Wood Mackenzie/SEIA, 2021). The distributed solar capacity in the U.S. is forecasted to triple over the next decade. The dramatic increase in distributed solar capacity has made it critical to understand the effects of these systems on existing electricity networks and markets. There are numerous areas where PV could have a significant impact on the distribution grid including: system reliability, resistive losses, peak load (which affects distribution capacity investments), voltage levels at the point of utilization, transformer aging, voltage regulator, mechanical wear, and the capability of protection systems to accurately identify fault (Cohen et al., 2016).

When PV are integrated into distribution systems, the conditions of power flow are fundamentally changed since power may be transferred from one customer to another or from the customers back to the grid. The ability of distribution systems to support

distributed solar capacity and the costs involved in doing so have raised concerns among distribution engineers, policy makers, and researchers. Solar rooftops cost over three times more than utility scale solar (Lazard, 2021), but advocates of distributed PV often argue that savings in transmission and distribution costs from generating electricity at the location where it is used are often not included in a simple cost comparison. The impact of distributed solar on future transmission and distribution costs is highly disputed.

One component of these costs and benefits are the reliability impacts of installed solar capacity on the grid. Over 90 percent of the outages experienced by customers are due to interruptions on the distribution grid (Joskow, 2012). Outages are costly; cost estimates of yearly outages range from \$18 billion to \$70 billion, after accounting for inflation, due to the effects of outages on everyday living, health and safety support services, communities, and the economy (Campbell, 2012). Reliability is a key metric for utility performance, and utilities annually make substantial investments to maintain system reliability. Installed solar capacity on the grid may impact this reliability in a number of ways; variable and intermittent solar energy can cause voltage and frequency variability which can lead to loss of load (EPRI, 2021). On the other hand, solar installed on the grid can help reduce peak load requirements, line loading, and equipment wear and tear, thereby reducing grid stress and improving system reliability (Horowitz, 2018).

In our research, we examine the impacts of installed solar capacity on the distribution grid, more specifically, this research paper focusses on understanding the reliability impacts of distributed solar on the grid. The objective of this research is to investigate the relationship between distribution grid reliability and distributed solar capacity on the grid by using detailed proprietary utility feeder data. More specifically the research answers the following questions:

1. Does distributed installed solar capacity on a feeder effect the duration and number of interruptions a feeder experiences?
2. What are the existing heterogeneities that we can observe across feeders serving

different population sizes?

The methodological approach we have taken in this paper to quantify the relationship between distribution grid reliability and distributed solar capacity is econometric. Solar capacity installations on a feeder may not be randomized for communities or households, therefore, they could be endogenous with reliability of feeders, which can give us biased estimates. Endogeneity could exist due to a variety of reasons, including, omitted variables such as socio-demographics factors which influence both feeder solar capacity installation and reliability; or due to biased sampling (less reliable feeders have higher costs to install solar capacity); or self-selection of samples (households on less reliable feeders choose to adopt solar). An empirical identification strategy based on use of instrumental variables is used in our research to deal with the existing endogeneity. The instrument we use to identify solar installed on a feeder is a shift-share instrument which is a product of solar irradiance at the feeder location and the cost of solar modules over the 8-year timeframe. The instrument is an interaction between a cross-sectional source of variation and a common time trend, and for this type of instrument the main identifying variation of the instrument comes from variation in the cross section i.e., average solar irradiance. This instrument directly impacts the solar installed on a feeder, however, it does not influence the reliability of the feeder, except through the solar installation capacity on a feeder. We use proprietary feeder level data on solar installation capacity and reliability from a large investor owned utility within one state of the United States for its utility service territory over the state for 8 years between 2013 – 2020 which is mapped to the zip code and merge it with demographic and weather datasets at the zip code and county level respectively, in our research.

In our results we estimate positive causal effects of distributed solar on feeder grid reliability metrics. More specifically, we see that presence of solar capacity on a feeder, can help reduce outage duration on the feeder. This relationship is dependent on the number of customers on the feeder. Low population feeders see improvements in reliability, with

installation of solar capacity. This effect reduces as the populations on the feeder increase. In our dataset, almost 79 percent of the total number of feeder-years, saw an improvement in reliability with reduced duration of interruptions due to presence of solar capacity on the feeder. Further, we did not find any relationship between solar installations, and the number of interruptions on a feeder. These were found to be primarily dependent on weather related factors, primarily precipitation.

The contribution of this paper to the existing literature is multifold. First, it contributes to literature which evaluates the impacts of distributed solar on the distribution grid (Astier, et al., 2021; Beach and Mcguire, 2017; Brown et al., 2001; Cohen, et al., 2016; Cohen and Callaway, 2013; Hoke et al., 2013; Keyes and Rabago, 2013; Paatero and Lund, 2007; Piccolo and Siano, 2009; Quezada et al., 2006; Wang et al., 2009; Wide n et al. 2010; Woyte et al., 2006). Existing engineering studies which explore these impacts often depend on data which does not capture the true complexity of the grid topology and the socio-economic context associated with it. Further, transmission and distribution costs or benefits of distributed solar, while highly debated, are not well studied in existing literature (Borenstein,2020; Sexton et al., 2021; Lucas, 2018). Secondly, studies that do evaluate impacts of distributed solar considering grid complexities, have not considered grid reliability impacts in their research (Astier, et al., 2021; Cohen, et al., 2016). Further, our research provides methods and estimates of this impact using actual feeder data, which can be potentially used to calculate related costs and benefits for the distribution grid. Third, we make our estimations using a unique panel dataset of feeder level reliability and solar installations, which captures varying climates, loads supplied and feeder topology. This is particularly important since existing research typically relies on simulated data of a single feeder or feeder types or climate. Our research is based on data over 8 years for over 560 feeders in the utility service territory of a large investor-owned utility in the United States, thereby capturing varying load types, feeders, climates, and demographics. Use of actual feeder data which captures grid complexities, makes our results generalizable and applicable in different policy contexts.

This paper is divided into six parts. Section 2 summarizes the background of the technical impacts of distributed solar on distribution grid reliability and distribution grid reliability metrics. Section 3 reviews the literature on the topic. Section 4 addresses the methodology, including the data and the empirical strategy. Section 5 discusses the results, and section 6 presents the conclusions.

4.2 Background

4.2.1 Impact of distributed solar on reliability

Several factors can influence the reliability of the grid due to the presence of solar installation capacity on the grid. First, under certain grid situations, standard distributed solar in regular operation (as well as substandard and aberrant distributed solar) might affect grid voltage. These violations and faults may cause local overvoltage or overvoltage at isolated feeders and substations, or local undervoltage from a unit trip, with catastrophic implications in a low-inertia environment with limited security margins and rapid clearing requirements (EPRI, 2021). Second, planners note that intermittent, variable, and irregular local power flows from distributed solar in regular operation (as well as inferior and abnormal distributed solar) might impair system frequency. A remote fault can lead to underfrequency, or a transmission fault can lead to over frequency. Both, voltage, and frequency issues can lead to loss of distributed solar generation and load (EPRI, 2021). On the other hand, distributed solar has peak clipping effect. It can help reduce overall loading on a feeder, especially during peaks, thereby reducing the line load, and improving system reliability (Li and Lui, 2012). Distributed solar can provide additional capacity to the feeder or substation. This helps feeders that are short of capacity or have aging infrastructure, thereby reducing stress on these systems and improving grid reliability.

The effect of solar installed capacity on the duration of interruptions on a grid depends on how a solar system operates on the grid during an outage. A solar PV system built with the intention of providing energy during a utility power outage must be capable of isolating itself from the grid, maintaining power generation, and storing any surplus for later use.

Current operational regulations necessitate that grid-connected solar PV systems immediately cut off from the grid during an outage for safety reasons. Most of these setups are not designed to work either off the grid or with a connection to the grid during an interruption. As a result, they stop producing electricity altogether and disconnect from the grid if there is a disruption in the system. In addition, most existing PV systems are not combined with batteries or an auxiliary power source (such as a backup generator) to enable them to provide continuous electricity to a load.

In our research the utility under consideration requires all distributed solar systems to be “non-islanding”¹ as per IEEE 1547. Since a solar PV on a feeder is disconnected during an outage, it does not provide any benefits to the grid during that timeframe. Further, when a large quantity of distributed solar disconnects from the grid at once, it may cause grid stability issues. Similarly, if a large quantity of distributed solar reconnects to the grid at once after an outage, or increases its power output at a steep rate, it can cause grid stress. This shows that presence of solar installation capacity on a grid is likely to have no effect or increase the duration of interruption on the grid.

4.2.2 Distribution grid reliability metrics

To understand distribution grid reliability, it is key to understand the different types of interruptions, and the metrics used to measure distribution grid reliability. The standards to measure interruptions are defined by IEEE Standard 1366-2012. Momentary interruptions are interruptions that are 5 minutes or less, while any interruption to a customer lasting longer than five minutes, regardless of the reason or origin, is referred to as a sustained electric service interruption (SESI). These interruptions are further classified based on their source of origin i.e., 1) bulk service interruptions originating at an electric power generating facility or electric power transmission system; 2) substation interruptions which start at substations, and 3) distribution system interruptions (DSI) which begin at the primary or secondary voltage electric distribution system.

¹During islanding, a distributed generator (DG) provides electricity to a facility even after the local power grid has been cut off. Utility employees may not know a circuit is still energized during islanding, and therefore it can be dangerous.

DSI is further subdivided into two parts based on a major event criterion: 1) Major event day interruptions include DSI that commence on a major event day². 2) Common distribution interruptions (CDI) include any other DSI which do not occur on a major event day. These CDI are further subdivided into ordinary and extraordinary interruptions. Extraordinary interruptions are defined as interruptions which qualify for certain criterion under 8 categories which are interruptions that are planned, safety related, or government related, or caused due to public damage, vandalism, war, terrorism, emergency, or catastrophic events, or are special interruptions declared by the state utility commission. Any CDI which does not fall in the category of an extraordinary interruption is considered as an ordinary interruption. Summarizing, any interruption originating at the distribution system, which is not a major event day interruption or an extraordinary interruption, is considered an ordinary interruption. ODI can have several varying causes, such as weather-related events, equipment failure, peak loading conditions, tree or animal caused outages, vehicle accidents etc³.

Utilities may use a variety of metrics to measure and report their reliability performance. The most common metrics used for evaluating utility reliability performance are System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI). These metrics are often reported at the feeder, substation, and regional level by the utility. In our research, we consider reliability metrics at the most granular level available, i.e., the feeder level. These metrics are reported for all sustained electric service interruptions.

SAIDI calculates the average total number of minutes that each customer experiences without electricity throughout a specific time. Within SAIDI, we focus on interruption

²Major events relate to sporadic occurrences that are frequently brought on by severe weather, such as times when the utility encounters extreme stresses to its physical system or lacks the operational capacity to respond to those stresses. Because major events can vary greatly in quantity and severity from year to year, utilities typically provide SAIDI and SAIFI with major events omitted for direct comparison and study of year-over-year trends in reliability. Major event days are decided annually using historical distribution system interruption data and are determined in accordance with IEEE Standard 1366-2003.

³While no systematic analysis was done to study the causes of these interruptions for our dataset, we reviewed the utility's plans, over ten years, which provide annual reports and qualitative summaries of outages across different regions, gives us some insights into these possible causes.

minutes due to ODI. It is defined as:

$$SAIDI(ODI) = \frac{\sum Total\ interruption\ duration}{\sum Total\ number\ of\ customers} \quad (4.1)$$

Higher values of SAIDI (ODI) suggest that the feeder is less reliable than another feeder with lower values of SAIDI because they correspond to more interruption minutes that all customers, on average, experience.

SAIFI counts the average number of power outages that each customer encounters throughout a specific timeframe. It is defined as:

$$SAIFI = \frac{\sum Total\ number\ of\ interruptions}{\sum Total\ number\ of\ customers} \quad (4.2)$$

Similar to SAIDI, a greater value of SAIFI implies that the feeder is less reliable than a feeder with a lower value of SAIFI since a higher value of SAIFI corresponds to more interruptions experienced by all consumers, on average.

For our research one of the key metrics, we focus on is SAIDI (ODI) which is a primary measure of system average reliability performance for the utility. We consider this metric as distributed solar is most likely to impact outages at this distribution system, which are not caused due to major or extraordinary events. Thus SAIDI (ODI) is a good reliability metric to measure impacts on distributed solar on the distribution grid. We also consider SAIFI as a key metric to measure distributed solar impacts on the distribution grid. However, unlike SAIDI (ODI), the SAIFI metric is for all interruptions which a feeder experiences. The data on SAIFI for ODI was not available. However, research by EPRI shows that over 90 percent of all outages experienced by retail customers are distribution system outages (EPRI, 2011). We see similar trends in our data, since on average, SAIDI (ODI) makes up more than 88 percent of SAIDI (number of minutes).

4.3 Literature Review

Several studies have quantified the different effects of PV in distribution systems (Cohen and Callaway, 2013; Hoke et al., 2013; Paatero and Lund, 2007; Quezada et al.,

2006; Woyte et al., 2006; Wide n et al. 2010). Early studies on the topic, in 2000, treat distributed generation as dispatchable unit, while ignoring their intermittent nature. (Brown et al., 2001; Piccolo and Siano, 2009; Wang et al., 2009). Research in the area has frequently focused on a single or small number of distribution networks and often studies optimization of the placement and sizing of distributed generation while disregarding the interactions between various grid-connected users and the intricate grid topology (Beach and Mcguire, 2017; Keyes and Rabago, 2013). These studies often use the net in-feed method for analysis, where the difference between various demand profiles and simulated solar PV power derived from hourly solar irradiance data, is used to quantify the impact of distributed solar on the distribution network. It can be challenging to extrapolate from these case studies, though, given how varied distribution networks are in terms of topology, climate, and loads supplied. More recent publications (Cohen et al., 2016; Nguyen et al., 2016) model how distributed solar affects distribution network metrics in various feeder types and locations.

Further, translation of the complete range of engineering implications of distributed solar on distribution networks into economic values has received limited attention in research. Some engineering studies research the potential for distributed generating investments to postpone transmission and development investments and propose methodologies to quantify transmission and distribution deferral benefits (Gil and Joos, 2006; Mendez et al., 2006). For example, Darghouth et al., (2010), California Public Utility Commission (2013), and Beach and McGuire (2013) investigated the potential impact of solar adoption on California's distribution capacity upgrades. These approaches estimated how much distributed generation reduces peak net load, where net load is calculated as total demand minus distributed generation. However, typically such studies do not evaluate the value of PV at the feeder level, and for different quantities of solar installations on a feeder. The paucity of academic literature on transmission and distribution cost avoidance by distributed solar has been highlighted by researchers (Borenstein, 2020; Sexton et al., 2021). The sub-transmission and distribution grids, and

associated costs, are not taken into consideration by even the most recent studies that examine the regional variability in the social value of intermittent renewable technologies (Callaway et al., 2018; Fell et al., 2021; Sexton et al., 2021), mostly due to the difficulties in acquiring access to the essential data over a broad service territory.

Some engineering studies have investigated reliability impacts of distributed generation. However, a majority of these studies evaluate islanded operations of distributed solar systems during an outage. These studies show the potential benefits that solar PV systems can have on distribution grid reliability (Neto et al., 2006; Falaghi, and Haghifam, 2005; Faza, 2018; Da silva et al., 2012; Sun et al., 2015; Ngaopitakkul et al., 2013). For e.g., the research in Da silva et al., 2012 examines the increase in distribution system reliability brought by distributed energy resources, which enable certain feeders in the network to move their loads to other feeders. To enhance the performance and reliability of the network, Sun et al., 2015 create an algorithm for power balancing among renewables, storage, and flexible load. Faza, 2018 finds that distributed solar on the grid can help improve reliability and optimizes PV penetration to maximize reliability.

Two studies assess the value of distribution grid gains by distributed solar closely and relate to our work (Astier, et al., 2021; Cohen, et al., 2016), however these studies do not research the impact of distributed solar on reliability of the feeder and the value that may be derived from that. Astier, Rajagopal, and Wolak, (2021) estimate how the annual distribution of net injections at a distribution network substation are impacted by investments in five types of distributed generation technologies: solar PV, wind, small hydro, renewable thermal, and non-renewable thermal. They use a panel dataset of distributed generation units and hourly net injections to the electricity grid at over 2,000 local distribution networks throughout France for 2005-2018. They discover that investments in distributed wind and solar capacity have little to no effect on the yearly peak of hourly net injections to the distribution grid, whereas investments in distributed hydroelectric and thermal power have a considerable reduction in that peak. Additionally, they contend that unless distributed generation is supported by storage devices, an

increase in distributed solar PV and wind capacity in France is more likely to necessitate an increase in future network investments than a decrease in them.

Another study, Cohen, Kauzmann, and Callaway, 2016, quantifies the effect of distributed PV on the costs of operation and maintenance of distribution systems. They use 15-minute data on 7,000 California rooftop solar systems provided by Solar City, and historical financial data on distribution system costs from PG&E, a California utility. They find that PV on average has a small distribution circuit capacity deferral value, further, 90 percent of the feeders do not receive any distribution capacity upgrade benefit from PV, while 10 percent of feeders receive some value, at low penetrations. They also find that these benefits decline relatively quickly, as additional PV is installed on a circuit.

4.4 Methodology

4.4.1 Data

To identify the causal relationship between distributed solar installations and reliability of the distribution grid we use feeder-level data on reliability metrics and distributed solar installations for the utility territory of a large investor-owned utility within one state of the United States. The panel data for eight years spanning from 2013 to 2020 are used. The solar data by feeder by year includes PV systems installed at the premises of residential and non-residential customers by year. Distributed PV systems were present on 696 of the utility’s feeders through the end of 2021. These data were obtained from the utility’s Salesforce, system of record for distributed PV interconnections. The year denotes the date on which the end-use customer or its PV installer created the interconnection application request in utility’s online Salesforce portal⁴. The solar installed kW capacity is the name plate capacity on a DC basis for the systems installed on a feeder.⁵ A cumulative value of total solar capacity on a feeder (based on the current and

⁴This date was used due to best data availability and for maintaining consistency through the years. (Utility communication).

⁵Because historical BTM PV data on nameplate capacity was available more comprehensively and with higher quality on a DC basis than an alternating current (AC) basis, capacity, this data was used. The company uses 80% of the DC rating to convert to AC, which is what we have used, wherever conversions were required.

previous years) each year is used. The reliability data by feeder includes reliability metrics i.e. SAIDI, SAIFI, and SAIDI ODI on feeders across the utility territory. All feeders that had an outage during the time frame were included in the dataset. Some feeders were in and out of service during this time frame and were treated as not applicable (NA) when they were not in service. In cases where new feeders were added during the timeframe, the reliability metric for the previous years are listed as NA. If a feeder was retired during the year and had no customers at year end, the indices for that year would be listed as “NA”. The number of customers were based on year end premise counts. These datasets were merged with a geographic dataset which provided the inter-relationships between the feeders and the zip-codes on which the feeders are located.

Table 4.1: Summary statistics

Variable	Mean	Std. Dev	Min	Max
Solar installed capacity (kW)	531.136	634.2909	0	6794.69
SAIDI(ODI)	73.81	97.46519	0	1434.71
SAIFI	0.8233344	1.068731	.0003551	36.73856
Number of customers	2169.405	1393.618	14	7813
IV	29.77091	8.80278	16.56322	49.52632

Notes: The unit of analysis for the dataset is feeder years. These summary statistics are for 4,480 observations in our dataset.

Table 4.1 reports the mean, deviation, minimum, and maximum of the main variables of interest for 4,480 observations, where the unit of analysis is a feeder-year. This table shows that on average a feeder has 531 kW of solar capacity installed in a year, and it ranges between 0 and 6,795 kW. On average 2,169 customers are connected to a feeder in a given year, but the number of customers per feeder per year ranges from 14 to 7,831. The mean SAIDI (ODI) duration in minutes is 73.81 minutes and ranges between 0 and 1435 minutes on a feeder in a year, while the average for SAIFI per feeder per year is 0.82 interruptions and it ranges between 0 and 37 interruptions. Figure 4.1 and figure 4.2 presents the histogram for our dependent variables i.e., SAIDI (ODI) and SAIFI by year

respectively.

Figure 4.1: Histogram of SAIDI(ODI)

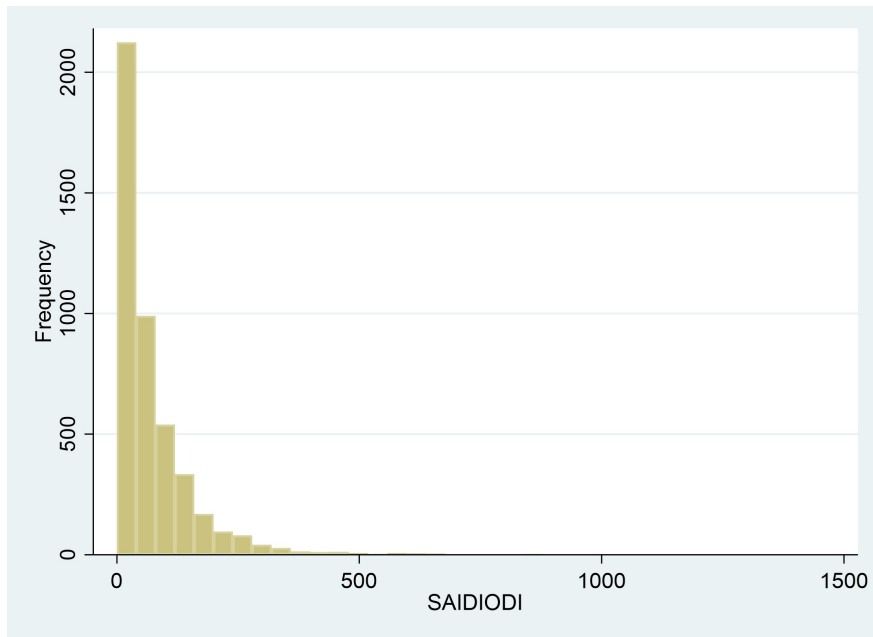
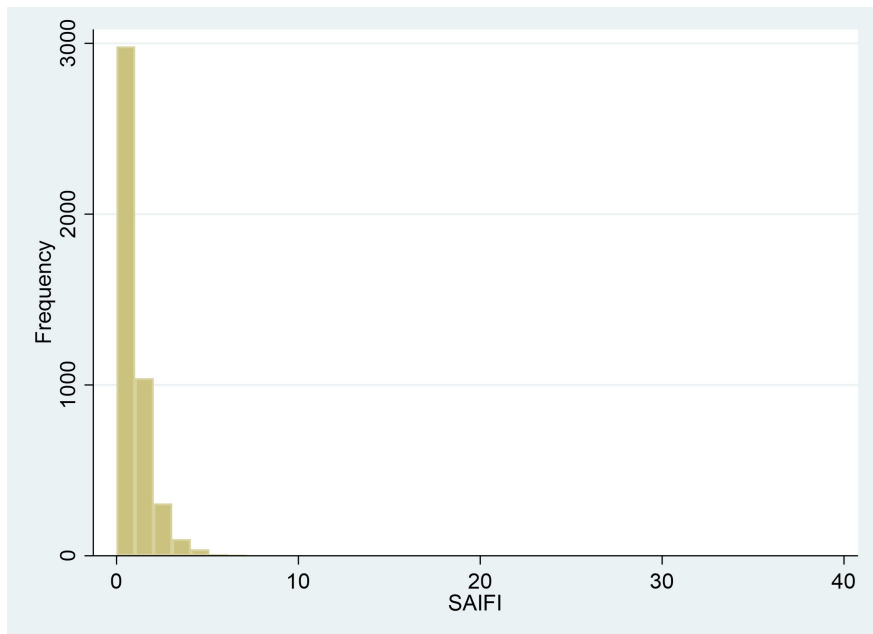


Figure 4.2: Histogram of SAIFI



For our demographic controls we used zip code level data from the American Community Survey five-year datasets for the years in the time frame studied. For our weather-related controls we used two databases, storm data and the PRISM data. The

storm data which is published by the National Oceanic and Atmospheric Administration (NOAA) documents the occurrence of storms and other weather phenomenon (NCDC, 2022). This dataset was used to gather wind data primarily, it captures the magnitude of the wind speed in knots during extreme wind events such as high wind, storm wind, and thunderstorm wind. This data was available on a county and zone (developed by the National Weather Service) level and was mapped to zip codes⁶. The PRISM dataset developed by the Oregon State University was used to gather data on the annual total precipitation which includes rain and melted snow, based on the zip code centroid coordinates (PRISM Climate Group, 2022). This dataset was also used to gather data on annual daily average of solar radiation received on a horizontal surface which was used as part of the instrument. The complete dataset with the dependent, independent and control variables, had data on 560 feeders i.e., 74 percent of the total feeders in the utility service territory over 8 years, and 4,480 observations in total.

4.4.2 Empirical methods

our empirical analysis, we are interested in estimating the effect of distributed solar installations on the distribution network reliability in feeder f in year t . The dependent variable in our analysis, is the annual change in the system average interruption duration index for ordinary duration interruptions (SAIDI (ODI)), and the system average interruption frequency index (SAIFI) in feeder f in year t .

We use the inverse hyperbolic sine transformation, also known as arcsinh, for our dependent variables. These variables (SAIDI (ODI) and SAIFI) are left skewed and have a large number of zero values (Figure 4.1 and 4.2). The arcsinh transformation has gained favor among applied economists recently since it resembles a logarithm and it allows for the retention of zero-valued (and even negative-valued) observations (Bellemare, and Wichman, 2020).

For a random variable x , taking the inverse hyperbolic sine transformation yields a

⁶County and zone mapping to zip codes was done by intersecting shapefiles of counties and zones with the shapefile of the centroids of the zip codes being considered (based on shapefiles used by NOAA in their analysis).

new variable \bar{x} , such that:

$$\bar{x} = \operatorname{arcsinh}(x) = \log\left(x + \sqrt{x^2 + 1}\right) \quad (4.3)$$

We also mean centered our interaction terms to enable ease in interpretation of coefficients. We estimate the empirical specification denoted by equation 4.4 and 4.5.

$$\begin{aligned} \operatorname{arcsinh}(\operatorname{SAIDI}(ODI)_{ft}) = & \alpha + \delta_t + \delta_f + \beta_0 kW_{ft} + \beta_1 Cust_{ft} \\ & + \beta_2((kW - kW_{mean})_{ft} * (Cust - Cust_{mean})_{ft}) + \gamma X_{zt} + \varepsilon_{ft} \end{aligned} \quad (4.4)$$

$$\begin{aligned} \operatorname{arcsinh}(\operatorname{SAIFI}_{ft}) = & \alpha + \delta_t + \delta_f + \beta_0 kW_{ft} + \beta_1 Cust_{ft} \\ & + \beta_2((kW - kW_{mean})_{ft} * (Cust - Cust_{mean})_{ft}) + \gamma X_{zt} + \varepsilon_{ft} \end{aligned} \quad (4.5)$$

where kW_{ft} is the installed solar capacity on a feeder during a year; $Cust_{ft}$ is the number of customers on a feeder in a given year, and $kW_{ft} * Cust_{ft}$ is an interaction term of the number of installed kW and customers on a feeder in a given year. We add feeder fixed effects which control for within feeder changes such as load growth changes on a feeder. Year fixed effects control for time trends which may have an impact on the grid such as the average changes in electricity demand. The coefficient of interest is β_0 , which represents the effect of (additional) solar capacity on the network reliability metrics, β_1 represents the effect of additional number of customers on a feeder on the reliability metrics, and β_2 which represents the effect of the number of customers on a feeder, and the installed solar capacity on a feeder together. X_{zt} are demographic and weather controls collected annually at the county and zip code level.

The detailed and extensive data we have used allows us to absorb year, feeder, and substation fixed effects to credibly control for broader time trends and differences across feeders. However, endogeneity in the data, could bias the regression results. It is possible that an omitted variable, such as socio-demographic factors, could affect both reliability of a feeder, and solar installations on a feeder. Research has shown that power outages may last longer in communities with lower socioeconomic status or communities of color (Liévanos, and Horne, 2017; Román et al., 2019; Yabe and Ukkusuri, 2020) Also, we know

that socio-demographics play a key role in solar adoption across the country (Barbose et al., 2020; Lukanov and Krieger, 2019; Reames, 2020). Additionally, new research has shown that the existing technical limits of the electric grid infrastructure design can exacerbate existing inequities in DER adoption and hosting capacity of the grid can limit distributed solar PV adoptions in the country inequitably (Brockway et al, 2021). Therefore, an OLS estimate of β may suffer from omitted variable bias for example due to unobserved shocks to reliability arising from something like housing structure median age that has an effect on solar installations and reliability of households and businesses. Failure to capture all these socio-demographic factors, may lead to endogeneity issues in our regressions due to omitted variable bias. While we have controlled for some socio-demographic indicators, there may be some, that are not captured in these controls, and are omitted variables.

Another issue which may arise, is that older, less reliable feeders may have higher costs to upgrade, which can often be charged to the customer and are unobserved to the econometrician. These costs can act as a barrier to solar adoption in less reliable feeders, thus less reliable feeders are less likely to have solar installations. Without accounting for this sampling bias, we can overestimate the impacts of solar on reliability of the feeder.

Lastly, the decision to install solar capacity might be endogenous especially when the solar installation decision depends on the feeder reliability of the distribution network i.e., customers on less reliable feeders are more likely to adopt solar to improve power flow in their circuit.⁷ Concern over electricity reliability in a household, may induce a household to install solar. This can cause self-selection, which may lead us to underestimate the impacts of solar on reliability of the feeder.

We use a set of fixed effects and control variables that can reduce but not completely remove this possible bias. If the zip codes under consideration experience various shocks to their reliability over the investigation period and modify their solar adoption correspondingly, our estimates in Eq. 4 will be biased.

⁷To improve their household or business's reliability, they would be required to have solar systems with batteries, which can be used for power, when there is an outage in a household or business.

To deal with these endogeneity issues, we use an instrumental variable which should produce exogenous variation in solar installations and reliability on a feeder. We use a measure of the average solar irradiance on a horizontal surface to develop an instrument for the number of solar installations in a zip code in the utility territory. We interact this time-invariant variable at the zip code level with time-varying shocks in the global price of solar panel modules to develop an instrument for zip code level installation a common time trend variable (time variation in the cost of solar panel modules). The instrument Z_{zt} is defined in Equation 4.6.

$$Z_{zt} = Irradiance_z * \frac{1}{ModulePrice_t} \quad (4.6)$$

where $Irradiance_z$ is a time-invariant measure of the total global shortwave solar radiation on a horizontal surface.

A valid instrument needs to satisfy two conditions: that it is correlated to the endogenous regressor $Cov(Z, kW, \bar{Z} * (Cust - Cust_{mean})_{ft}) \neq 0$, and that it is not correlated to the error term $Cov(Z, \varepsilon) \neq 0$. The first stage regressions are presented in Table 4.2 and demonstrates a significant correlation between the IV and the endogenous variables. Further, we have also formulated the first-stage F-statistics for the regressions of all our results and these were found to cross the threshold in all specifications to ensure validity of the instrument. The median, mean and standard deviation of the IV are 28.26, 29.77 and 8.80 respectively, showing that there is substantial variation in the IV across zip codes.

The exclusion restriction requires that there is no direct effect of IV on the probability that a customer has lower or higher reliability. While this is not a Bartik style instrument, the instrument is an interaction between a cross-sectional source of variation and a common time trend. Goldsmith-Pinkham et al., (2020) demonstrates that in this situation, the instruments are numerically equivalent to using cross-sectional variation (interacted with time fixed effects when multiple periods are used) as instruments in a weighted GMM

Table 4.2: First stage OLS regression

Variable	Solar installed (kW)	Solar installed (kW)*Number of customers
IV	-51.172***	52,019.503*
IV*Number of Customers	0.005***	19.844***
Observations	4,480	4,480
R-squared	0.921	0.916

** p<0.01, * p<0.05, * p<0.1

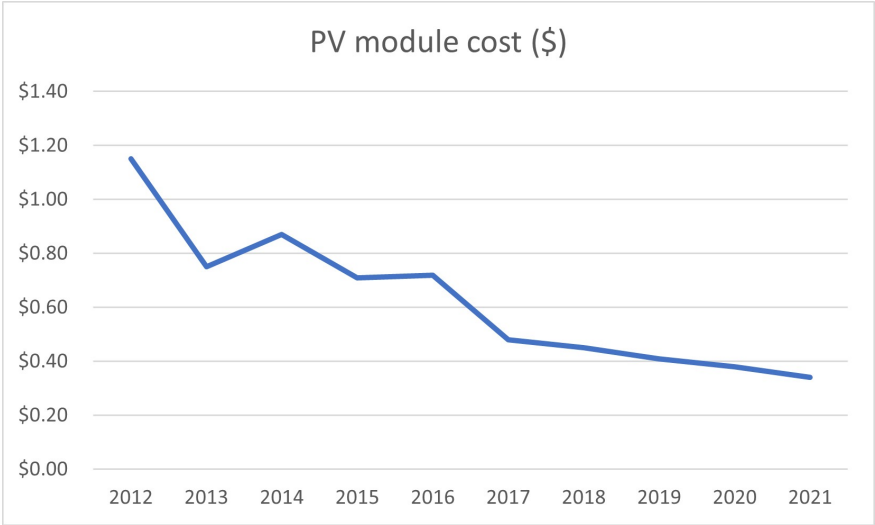
Notes: Robust standard errors clustered at the feeder level in parentheses.

estimation - and the shifts only provide the weights and affect the instrument relevance, but not the endogeneity. Goldsmith-Pinkham et al., (2020) use two key assumptions in their work. First, locations are independent and there are no spatial spillovers, and that second, the data consist of a series of steady states. Both assumptions are applicable in our case, and thus, drawing from their study in our setting, exogeneity relies on the cross-sectional variation. Identification relies on shocks to reliability being orthogonal to the irradiance in a zip code (Goldsmith-Pinkham et al.,2020). It measures the zip code level variation temporally which permits us to consider the time-variant unobserved heterogeneity for the panel dataset. The main identifying variation of the instrument comes from cross-sectional differences in the solar irradiance: specifically, variation in the average solar irradiance, i.e. the amount of energy from the sun hitting a given area of land. Similar shift share instruments have been previously used in literature (Beattie et al., 2019; La Nauze, 2021).

The logic of the research design is as follows: suppose there are two similar zip codes, however one has lower solar irradiance (control) while the other has higher solar irradiance (treatment). This solar irradiance on the zip code will affect the decision of a household or business to install solar. The area of the utility service territory spreads over the state and shows some variation in the irradiance. The time varying component of the instrument is the inverse of the PV module price which is the global solar panel module price index at year t. Figure 4.3 plots the value of this price over time. Identification then relies on there

being no unobserved time-varying differences across two zip codes that are correlated with factors that might simultaneously drive solar panel installation and reliability. Solar irradiation is unlikely to be driven by factors correlated with reliability. For example, if changes in solar irradiance which cause solar flares or solar storms increases outages, we might expect areas which receive higher solar irradiance to have higher number and duration of outages. However, firstly, historically, power outages due to solar flares or solar storms recorded have been very rare (U.S. Department of Commerce, 2018). Secondly, we use averages of solar irradiance at a zip code, which is based on data of solar radiation normal for the past 30 years ranging from 1991—2020, thereby, it does not capture the extremes in the solar irradiance which may cause a solar storm like events. Also, since we use a time invariant measure of solar radiation at the zip code level, so the identification does not come from changes in solar radiation over the sample period. It therefore seems plausible that there is no causal relationship between shocks to electricity reliability and average zip code solar irradiance.

Figure 4.3: PV module costs over time (Source: EIA)



Our identification strategy would fail to account for time varying unobserved characteristics of electrification if our instruments are not exogeneous. We argue that the instrument i.e., the term obtained by interacting solar irradiance in a zip code, and a time

trend i.e. the cost of solar PV modules, does not affect reliability directly. Because we include feeder and time fixed effects, we can control for local, unobserved feeder fixed effects. Further, we report the instrument test statistics ensure the strength and relevance of our instruments for all specifications. A test for under identification was performed which examines whether the instruments are correlated with the endogenous regressor(s). The test is implemented by Kleibergen-Paap's LM statistic, under the null hypothesis that the equation is under-identified, that is, instruments do not affect the endogenous variables significantly. As shown in the results section, the null hypothesis is rejected for all our specifications, that is, the instruments are relevant.

4.5 Results and discussion

The results of the impact of distributed solar on reliability of the distribution grid have been presented in Table 4.3 to Table 4.7. Table 4.3 presents results of our main specification. Table 4.4 and Table 4.5 present results are OLS estimations for impacts of solar installed kW for SAIDI (ODI) and SAIFI respectively. Table 4.6 and Table 4.7 presents results for impacts of solar installed kW with IV fixed effects specifications for SAIDI (ODI) and SAIFI respectively. All result regression specifications have feeder and year fixed effects along with additional independent variables as described in the empirical model. Robust standard errors clustered at the feeder level are calculated for all coefficients.

Investigating our main specification in Column 1 in table 4.3, which uses an IV-FE model, we see that as the solar installed capacity on a feeder increases by 100 kW the average duration of interruption decreases by 20 percent, and this relationship is statistically significant. If the number of customers on the feeder increases by 1000, it increases interruption duration by 26 percent.

The annual precipitation also increases the duration of interruption by 0.1 percent. In our IV-FE estimation for SAIFI (column 3), only annual precipitation magnitude has a significant effect on the number of outages on a feeder. In our OLS estimation, for both

Table 4.3: Impact of solar installed kWm on average reliability metrics

	(1)	(2)	(3)	(4)
	IV-FE	OLS	IV-FE	OLS
Per 100 kW	-0.205*	0.003	-0.039	0.007
	(0.096)	(0.013)	(0.038)	(0.005)
Per 100 kW × Per 1000 customers	0.063*	0.005	0.012	0.000
	(0.027)	(0.006)	(0.011)	(0.003)
Per 1000 customers	0.255*	0.087	0.048	0.011
	(0.119)	(0.058)	(0.050)	(0.033)
Max win magnitude	0.000	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Annual precipitation	0.001**	0.001**	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Population above 200 percent of FPL	-0.016	-0.003	-0.005	-0.002
	(0.010)	(0.007)	(0.005)	(0.004)
Percent of black population	0.012	0.003	0.008	0.007
	(0.032)	(0.026)	(0.014)	(0.013)
Percent of hispanic population	-0.007	-0.007	-0.000	-0.000
	(0.010)	(0.009)	(0.004)	(0.004)
Percent of owner occupied households	0.013	0.010	0.006	0.006
	(0.008)	(0.007)	(0.003)	(0.003)
Median year of built structures	0.008	0.018	-0.001	0.002
	(0.014)	(0.011)	(0.007)	(0.006)
Number of observations	4480.000	4480.000	4480.000	4480.000
R-squared	-0.117	0.010	-0.020	0.010
First stage F-statistic	21.766	.	21.766	.
Underidentification LM statistic p-value	0.000		0.000	

Standard errors in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)

Notes: Column 1 and 3 are IV-FE estimations while column 2 and 4 are OLS estimations. Column 1 and 2 use $\text{arcsinh}(\text{SAIDI (ODI)})$ as the dependent variable, and column 3 and 4 use $\text{arcsinh}(\text{SAIFI})$ as the dependent variable. These estimations measure impacts of solar installed kW for SAIDI (ODI) and SAIFI. The interaction term is mean centered. The unit of analysis is feeder-year. All regressions include plant fixed effects and year fixed effects in addition to the variables shown. Robust standard errors are clustered at the feeder level.

Table 4.4: Impact of solar installed kW on average reliability metrics - SAIDI(ODI) - OLS

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
Per 100 kW	0.006 (0.011)	0.004 (0.011)	0.006 (0.011)	0.002 (0.013)	0.003 (0.013)
Per 1000 customers		0.090 (0.057)	0.089 (0.057)	0.092 (0.057)	0.087 (0.058)
Max win magnitude			0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
Annual precipitation			0.001*** (0.000)	0.001*** (0.000)	0.001** (0.000)
Per 100 kW × Per 1000 customers				0.005 (0.006)	0.005 (0.006)
Population above 200 percent of FPL					-0.003 (0.007)
Percent of black population					0.003 (0.026)
Percent of hispanic population					-0.007 (0.009)
Percent of owner occupied households					0.010 (0.007)
Median year of built structures					0.018 (0.011)
Number of observations	4480.000	4480.000	4480.000	4480.000	4480.000
R-squared	0.004	0.005	0.008	0.009	0.010

Standard errors in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)

Notes: These are OLS estimations measuring impacts of solar installed kW for SAIDI (ODI). The dependent variable is $\text{arcsinh}(\text{SAIDI (ODI)})$. The unit of analysis is feeder-year. The interaction term is mean centered. All regressions include plant fixed effects and year fixed effects in addition to the variables shown. Robust standard errors are clustered at the feeder level.

Table 4.5: Impact of solar installed kW on average reliability metrics - SAIFI - OLS

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	FE	OLS
Per 100 kW	0.007 (0.004)	0.006 (0.004)	0.007 (0.004)	0.007 (0.005)	0.007 (0.005)
Per 1000 customers		0.010 (0.032)	0.009 (0.033)	0.010 (0.033)	0.011 (0.033)
Max win magnitude			0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Annual precipitation			0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Per 100 kW × Per 1000 customers				0.000 (0.003)	0.000 (0.003)
Population above 200 percent of FPL					-0.002 (0.004)
Percent of black population					0.007 (0.013)
Percent of hispanic population					-0.000 (0.004)
Percent of owner occupied households					0.006 (0.003)
Median year of built structures					0.002 (0.006)
Number of observations	4480.000	4480.000	4480.000	4480.000	4480.000
R-squared	0.005	0.005	0.009	0.009	0.010

Standard errors in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)

Notes: This is an OLS estimations measuring impacts of solar installed kW for SAIFI. The dependent variable is arcsinh(SAIFI). The unit of analysis is feeder-year. The interaction term is mean centered. All regressions include plant fixed effects and year fixed effects in addition to the variables shown. Robust standard errors are clustered at the feeder level.

Table 4.6: Impact of solar installed kW on average reliability metrics - SAIDI(ODI)- IV-FE

	(1)	(2)	(3)	(4)	(5)
	IV-FE	IV-FE	IV-FE	IV-FE	IV-FE
Per 100 kW	-0.216** (0.078)	-0.207** (0.074)	-0.166* (0.079)	-0.214* (0.101)	-0.205* (0.096)
Per 1000 customers		0.274** (0.096)	0.240* (0.096)	0.269* (0.126)	0.255* (0.119)
Max win magnitude			0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Annual precipitation			0.001** (0.000)	0.001** (0.000)	0.001** (0.000)
Per 100 kW \times Per 1000 customers				0.063* (0.028)	0.063* (0.027)
Population above 200 percent of FPL					-0.016 (0.010)
Percent of black population					0.012 (0.032)
Percent of hispanic population					-0.007 (0.010)
Percent of owner occupied households					0.013 (0.008)
Median year of built structures					0.008 (0.014)
Number of observations	4480.000	4480.000	4480.000	4480.000	4480.000
R-squared	-0.166	-0.146	-0.091	-0.129	-0.117
First stage F-statistic	27.765	31.052	23.639	23.547	21.766
Underidentification LM statistic p-value	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)

Notes: These are IV-FE estimations measuring impacts of solar installed kW on SAIDI (ODI). The dependent variable is $\text{arcsinh}(\text{SAIDI (ODI)})$. The unit of analysis is feeder-year. All models use interaction of average global horizontal irradiance at the centroid of the zip code of a feeder location and inverted solar module costs as the instrumental variable. The interaction term is mean centered. All regressions include plant fixed effects and year fixed effects in addition to the variables shown. Robust standard errors are clustered at the feeder level.

Table 4.7: Impact of solar installed kW on average reliability metrics - SAIFI- IV-FE

	(1)	(2)	(3)	(4)	(5)
	IV-FE	IV-FE	IV-FE	IV-FE	IV-FE
Per 100 kW	-0.053 (0.030)	-0.051 (0.029)	-0.029 (0.032)	-0.038 (0.040)	-0.039 (0.038)
Per 1000 customers		0.060 (0.042)	0.041 (0.044)	0.046 (0.052)	0.048 (0.050)
Max win magnitude			0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Annual precipitation			0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Per 100 kW \times Per 1000 customers				0.011 (0.011)	0.012 (0.011)
Population above 200 percent of FPL					-0.005 (0.005)
Percent of black population					0.008 (0.014)
Percent of hispanic population					-0.000 (0.004)
Percent of owner occupied households					0.006 (0.003)
Median year of built structures					-0.001 (0.007)
Number of observations	4480.000	4480.000	4480.000	4480.000	4480.000
R-squared	-0.055	-0.050	-0.013	-0.020	-0.020
First stage F-statistic	27.765	31.052	23.639	23.547	21.766
Underidentification LM statistic p-value	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)

Notes: These are IV-FE estimations measuring impacts of solar installed kW on SAIDI (ODI). The dependent variable is $\text{arcsinh}(\text{SAIDI (ODI)})$. The unit of analysis is feeder-year. All models use interaction of average global horizontal irradiance at the centroid of the zip code of a feeder location and inverted solar module costs as the instrumental variable. The interaction term is mean centered. All regressions include plant fixed effects and year fixed effects in addition to the variables shown. Robust standard errors are clustered at the feeder level.

reliability metrics only annual precipitation has significance, while the installed solar capacity kW does not show any effects on the reliability metrics. These results show us that the duration of an outage reduces as solar on the feeder increases and, and this relationship is dependent on the number of customers on a given feeder.

The results from the simple OLS estimation with feeder fixed effects and year fixed effects in Tables 4.4 and 4.5 show no statistically significant effect of solar capacity installed on a feeder. In these tables, across all columns, the effect of solar on the distribution grid is consistently insignificant. Further, the effect of the number of customers and the interaction term of the number of customers on a feeder and the solar capacity installed on a feeder (kW) are insignificant too.

Table 4.6 evaluates the local average effect of solar installed kW on a feeder on outage duration of the distribution grid feeder using the IV-FE estimation. Similarly, Table 4.7 evaluates the local average effect of solar installed kW on a feeder on number of outages on the distribution grid feeder using the IV-FE estimation. Table 4.6 uses arcsinh SAIDI (ODI) as the dependent variable, while Table 4.7 uses arcsinh SAIFI as the dependent variable. In Table 4.6 and Table 4.7, column 1 uses only the solar installed kW per feeder as the explanatory variable, column 2 uses solar installed kW and the number of feeder customers as the explanatory variables, column 3 additionally uses a mean centered interaction term of solar installed kW and the number of feeder customers as an explanatory variable, similarly, column 4 additionally uses weather controls and column 5 additionally uses demographic control variables in addition to the variables in the previous column. Feeder and time fixed effects are also included in these regressions in Table 4.5 and 4.6.

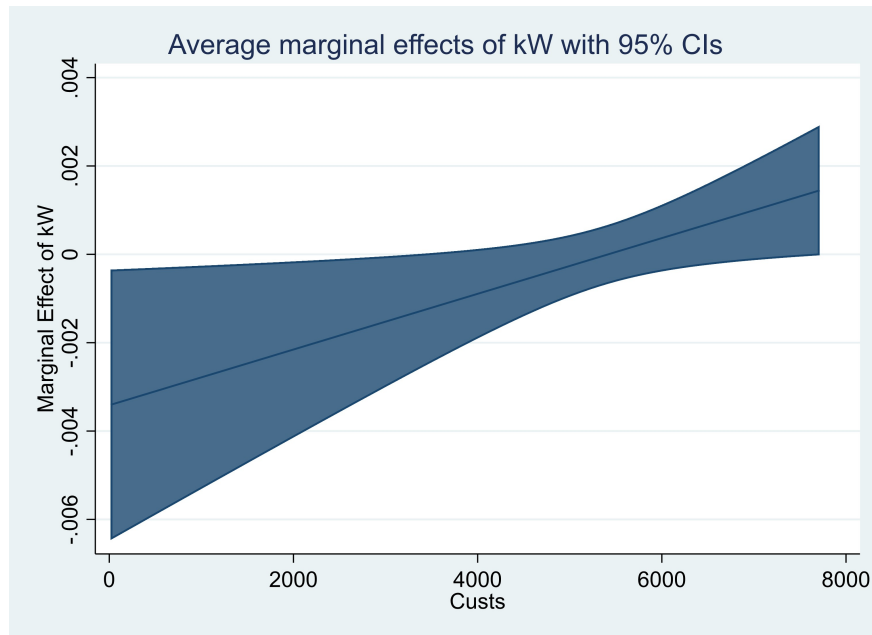
Table 4.6 shows us that an increase in solar installed kW on a feeder has a weakly significant negative effect on the duration of ordinary distribution interruptions. This translates to an improvement in reliability of the feeder with a reduction in the duration of the interruption for ODI. This effect is consistent as we add more controls and endogenous variables in Table 4.6. When we consider only the effect of solar installed kW on the

reliability of the feeder (column 1), this translates to an improvement in the interruption duration by 22 percent for every 100 kW solar capacity. This effect reduces to 21 percent as we add the number of customers per feeder as an explanatory variable (column 2). As we add our weather controls in column 3, we see a further reduction of the effect of solar installed kW on a feeder, on the reliability of the feeder, and a one unit increase in precipitation magnitude at a feeder, increases the interruption duration by 0.11 percent. In column 4 and 5, we add a mean centered interaction term of the solar installed kW and the number of customers per feeder, to understand the marginal effects of the solar installed kW per feeder based on the number of customers on the feeder. In these specifications, we see a weakly significant effect of the solar installed kW and the number of customers per feeder, along with a weakly significant effect of the interaction term. Interpreting the values in column 5, using our main specification we see a reduction in interruption duration of 20percent as 100 kW solar is installed on a feeder. With 1000 customers increasing on a feeder, it increases interruption duration by 25 percent.

To understand the interaction term further, we plot the marginal effect of a kW on the number of customers on a feeder (Figure 4.4). From this plot we see that for feeders which have less than 3,314 customers, as solar kW is installed on the feeder increases, its reliability i.e. duration of interruption reduces. Whereas for feeders which have populations over 3,314, this effect is insignificant. In our dataset, almost ~ 79 percent of the feeder years have customer numbers less than 3,314 customers.

Table 4.7 shows the impact of solar installed kW per feeder on the number of interruptions on a feeder, however these effects are not significant for all the variables, except for the weather control variables. Thus, the value of the effect of 100 kW increase in solar installed capacity reduces the number of interruptions on the feeder by 4 percent non-significantly (Column 5). A increase in the number of customers by 1000, increases the number of interruptions per feeder by 5 percent non-significantly. A per unit increase in the magnitude of precipitation at a feeder location increases the number of interruptions per feeder by 0.04 percent and is weakly significant.

Figure 4.4: Average marginal effects of mean centered solar capacity on feeder (kW) with number of customers per feeder



4.6 Conclusion

Distributed solar is increasingly being deployed across the United States, which makes it critical to understand its impacts on the distribution grid. We study the impacts that distributed solar may have on the distribution grid, especially on the reliability of the grid. We also examine the possible heterogeneities that can be observed across feeders serving different populations. With this research we contribute to growing literature which evaluates the impacts of distributed solar on the distribution grid (Astier et al., 2021; Astier, et al., 2021; Beach and Mcguire, 2017; Brown et al., 2001; Cohen, et al., 2016; Cohen and Callaway, 2013; Hoke et al., 2013; Keyes and Rabago, 2013; Nguyen et al. 2016; Paatero and Lund, 2007; Piccolo and Siano, 2009; Quezada et al., 2006; Wang et al., 2009; Wide n et al. 2010; Woyte et al., 2006). More specifically, we study impacts of distributed solar on distribution grid reliability, considering grid complexities which to our knowledge has not been explored previously in literature. Our research uses a unique panel dataset of proprietary utility data at the feeder level of reliability and solar installations which captures varying climates, loads supplied and feeder topology. The use of actual feeder

level data which captures grid complexities enables us to make conclusions which are generalizable.

Our findings suggest that distributed solar has a positive causal influence on feeder grid reliability indicators. Particularly, we see that solar capacity on a feeder may assist in shortening the length of outages on that feeder. The number of customers on a feeder influences the strength of this relationship. Increase in solar capacity can help improve reliability in areas with a low population density. As more customers are added to the feeder, the impact weakens. In our data set, the inclusion of solar capacity on the feeder increased reliability and decreased the length of interruptions in approximately 79% of the feeder-years. In addition, we could not identify any relationship between the number of interruptions on a feeder and the solar system capacity on the feeder. They were shown to be largely dependent on meteorological variables, especially rainfall.

In this work we sought to examine the relationship between solar installed capacity on a feeder and grid reliability. While we were able to identify the effects of solar installation capacity on grid reliability while controlling for endogeneity and found effects which showed a decrease in outage duration, dependent on the size of the customer base, there may also be some alternative implications of these finding. It is possible that as more solar is installed on a feeder and with increasing penetration levels, there are needs for feeder upgrades over time (EPRI, 2020; Horowitz et al., 2018). These upgrades could enable improved reliability in feeders over time. Feeder upgrade strategies depend on location, type, and control modes of the distributed solar, in addition to the characteristics of the distribution system. Further, investments on feeder upgrades are often determined on a case by case and system by system basis and the upgrades may differ on resource requirements, costs, and risks to cope with higher distributed solar penetration levels (Horowitz et al., 2019). Utilities undertake a hosting capacity analysis to examine grid availability while approving solar interconnection, which ensures that grid reliability is maintained, as penetration levels increase, and upgrades are minimized, however, solar installed capacity can trigger upgrade needs over time. Additionally, an alternative to

avoiding these feeder upgrades would be for the utility to limit the installation capacity on a feeder (Horowitz et al., 2019). Detangling these effects can be a good area of future research.

Notably, we have assessed the effects of distributed solar on distribution grid reliability. Similar effects of other behind the meter technologies such as battery storage (with and without solar) and electric vehicles also forms an important area for future research. While penetration levels of these technologies are currently low, they are expected to rapidly increase over the years. Further, these behind the meter technologies which serve as a load or generation source, may complement each other to reduce grid impact, and examining their effects in conjunction would be a potential direction for future work.

To meet their decarbonization goals, states will need to make tremendous investments in grid capacity, which will require both time and money to implement. As distributed solar continues to grow, hosting this capacity for desired generation and electrification needs will not happen simultaneously without massive investment in staff and resources. Our results can help grid planners and policy makers in appropriately valuing reliability and resiliency benefits of distributed solar resources while making these critical investment and policy decisions. Geo targeting of solar installed capacity and upgrade investments can provide key economic benefits to the utility and its customers. As an aging infrastructure and grid accommodates new distributed solar capacity, it will need investments and policymakers and regulators will need to establish criteria for which grid upgrades are worth increasing customer rates. While making these decisions considering reliability effects of distributed solar will be critical for reaching our goals of a clean energy future.

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APPENDIX–A

Table A.1: Summary Statistics: Rural 2005

Statistic	Mean	St. Dev.	N
Mean village access to electricity	0.656	0.301	12,210
Mean hours of electricity per day (at the village level)	9.569	6.352	12,210
Household - labor hours per year	984.119	693.257	12,210
Women - labor hours per year	533.889	716.486	12,210
Men - labor hours per year	1,215.312	980.018	12,210
Household - labor participation	0.670	0.362	12,210
Men - labor participation	0.727	0.427	12,210
Women - labor participation	0.461	0.485	12,210
Access to electricity	0.655	0.476	12,210
Hours of electricity	9.496	8.720	12,210

Table A.2: Summary Statistics: Rural 2012

Statistic	Mean	St. Dev.	N
Mean village access to electricity	0.785	0.230	11,721
Mean hours of electricity per day (at the village level)	10.780	6.132	11,721
Household - labor hours per year	1,149.159	725.456	11,721
Women - labor hours per year	624.984	759.180	11,721
Men - labor hours per year	1,395.692	995.589	11,721
Household - labor participation	0.703	0.329	11,721
Men - labor participation	0.750	0.398	11,721
Women - labor participation	0.497	0.473	11,721
Access to electricity	0.809	0.393	11,721
Hours of electricity	11.084	8.092	11,721

Table A.3: Summary Statistics: Urban 2005

Statistic	Mean	St. Dev.	N
Statistic	Mean	St. Dev.	N
Mean village access to electricity	0.865	0.104	6,470
Mean hours of electricity per day (at the village level)	16.049	5.136	6,470
Household - labor hours per year	994.294	719.501	6,470
Women - labor hours per year	277.370	675.682	6,470
Men - labor hours per year	1,563.998	1,162.738	6,470
Household - labor participation	0.444	0.305	6,470
Men - labor participation	0.659	0.432	6,470
Women - labor participation	0.157	0.347	6,470
Access to electricity	0.951	0.217	6,470
Hours of electricity	17.759	7.069	6,470

Table A.4: Summary Statistics: Urban 2012

Statistic	Mean	St. Dev.	N
Statistic	Mean	St. Dev.	N
Mean village access to electricity	0.890	0.077	7,839
Mean hours of electricity per day (at the village level)	15.716	5.129	7,839
Household - labor hours per year	1,199.430	779.615	7,839
Women - labor hours per year	418.114	795.352	7,839
Men - labor hours per year	1,727.925	1,127.322	7,839
Household - labor participation	0.522	0.311	7,839
Men - labor participation	0.703	0.396	7,839
Women - labor participation	0.231	0.393	7,839
Access to electricity	0.970	0.169	7,839
Hours of electricity	17.196	6.841	7,839

Table A.5: Summary Statistics: Urban Slums 2005

Statistic	Mean	St. Dev.	N
Statistic	Mean	St. Dev.	N
Mean village access to electricity	0.847	0.145	1,285
Mean hours of electricity per day (at the village level)	15.961	5.223	1,285
Household - labor hours per year	1,157.333	734.740	1,285
Women - labor hours per year	395.355	762.638	1,285
Men - labor hours per year	1,673.457	1,103.311	1,285
Household - labor participation	0.540	0.317	1,285
Men - labor participation	0.726	0.406	1,285
Women - labor participation	0.237	0.408	1,285
Access to electricity	0.866	0.341	1,285
Hours of electricity	16.302	8.436	1,285

Table A.6: Summary Statistics: Urban Slums 2012

Statistic	Mean	St. Dev.	N
Mean village access to electricity	0.907	0.063	405
Mean hours of electricity per day (at the village level)	17.120	5.104	405
Household - labor hours per year	1,315.624	683.708	405
Women - labor hours per year	424.054	770.810	405
Men - labor hours per year	1,975.329	1,039.644	405
Household - labor participation	0.561	0.273	405
Men - labor participation	0.783	0.345	405
Women - labor participation	0.236	0.392	405
Access to electricity	0.970	0.170	405
Hours of electricity	18.595	7.482	405

APPENDIX-B

Table B.1: Summary Statistics

Statistic	Mean	St. Dev.
Energy experience	4.725	1.520
Confidence	5.290	1.361
Employment	0.877	0.328
Baseline	0.078	0.269
Baseline – no rejection	0.087	0.282
Plea	0.081	0.273
Plea – no rejection	0.098	0.298
Upfront bonus	0.100	0.300
Upfront bonus - no rejection	0.092	0.290
Performance bonus	0.082	0.275
Performance bonus - no rejection	0.086	0.280
Bonus choice	0.142	0.350
Bonus choice– no rejection	0.154	0.361
Productivity	0.030	0.030
Finished	1.000	0.000
Effort (Time taken)	1,954.302	6,242.999
Completeness	0.439	1.052
Completeness pct deviation from mean	0.088	0.794
Completeness pct deviation from mean-by project	-0.080	1.112
Completeness Z score - by project	0.414	1.083
Validity	0.343	1.086
Validity Z score by respondent	-0.135	0.934
Validity pct deviation from mean	0.332	1.104
Accuracy	0.156	0.818
Accuracy pct deviation from mean	0.074	0.301
Accuracy Z score by respondent	-0.248	0.899
Accuracy- Year reporting	0.707	0.456
Levenshien score	0.521	0.387

Notes: The table shows the summary statistics for all workers who finished the task (N=1060). This sample has been used for the final results specification. This sample is different from the full sample, which includes workers who do not finish their task (N=1993).