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ESSAYS ON ELECTRICITY ACCESS AND ENERGY RESILIENCE.

by

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ABSTRACT

The availability of abundant energy plays a critical role in all economies. In developing countries, access to reliable energy is central to driving industrialization, and bolstering the service sector, which now contributes significantly to the gross domestic product of many developing countries. It is well established that for many countries, there is a nexus between energy consumption and economic growth. In the developed world, energy reliability and resilience are at the forefront of energy discourse. In this dissertation, we explore these distinct but interwoven areas of energy.

In Chapter 2, we investigate the relationship between power outages and business performance in middle-income countries with high electrification rate. This is important as attaining universal electrification is presumed to be the pinnacle of electrification goals, yet data shows that some firms in countries with a 100% rate of electrification still suffer outages. In Chapter 3, we study the economics of a novel technology, concentrating solar power (CSP) plant, estimating the additional revenues that ancillary services such as spinning reserves can generate for a CSP plant owner. In Chapter 4, we investigate the role of microgrids in providing energy equity through access and resilience for low-income communities. Finally, in Chapter 5, we dive deeper into the question from Chapter two, carrying out a case study on Tunisia to derive the causal effect of outages on firm productivity under conditions of universal electrification.

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To my dearest mother

CHAPTER 1
INTRODUCTION

Electricity reliability is important. Yet, the impacts of electrification on economic growth and development outcomes have been contested in development literature. While a number of experimental findings show that the benefits of electrification are not as large as previously thought [Burlig and Preonas, 2016, Lee et al., 2020], critics of this view argue that experimental studies consider only the short- to medium-run effects of electrification projects, often in rural areas. The first part of this dissertation argues that the impact of electrification in rural areas is potentially different from that in industrial settings. In particular, the first paper examines how power outages affect firm performance in countries with universal electrification, defined as the attainment of a 100% rate of electrification in both urban and rural areas in a given country.

Many middle-income countries have reached a 100% rate of electrification — a milestone that developing countries aspire to. Universal electrification has been framed by policy makers and development institutions as the pinnacle of electrification goals, often without adequate emphasis on reliability. It is clear, however, from this study that universal electrification does not always translate to reliable power supply to industry. In fact, many firms in the four middle-income countries we study — Egypt, Indonesia, Morocco, and Tunisia — still cite electricity as some form of obstacle to firm operations. About 20% of all firms in our sample of over $8,000$ firms still experience power outages. Outages in these countries average two to three on a monthly basis, with some outliers. More so, some firms are compelled to invest in self-generation.

The questions we ask include: Do firms that suffer outages in these countries also suffer productivity losses relative to those firms that do not suffer outages? Secondly, how effective is universal electrification in shielding firms from losses? We find that there is cause for optimism as two countries in our sample show no effect of outages on firm performance. However, there is significant heterogeneity in our results as we find that firms experiencing outages in both Tunisia and Egypt suffer significant losses. Our conclusion is that while universal electrification is a worthwhile development goal, it should be considered in concert with investments in reliability.

In our second paper, *Estimating the Value of Concentrated Solar Power with Ancillary Services*, we also emphasize the importance of reliability one the one hand, and the potential of CSP to increase the revenue of a plant owner by providing ancillary services on the other. Ancillary services include a range of offerings such as spinning reserves, non-spinning reserves, firm capacity, and regulation control. These services are available as contingencies to ensure that there is a balance in the supply and demand of electric energy. Spinning reserves are contingency services that could be called upon at any time to provide electric energy within a time period of 10 minutes. In particular, we focus on the provision of spinning reserves to the Independent System Operator. The task of providing this priced service is usually reserved for conventional sources of electricity generation. But the dispatchability of CSP makes it unique in comparison to other sources of variable generation. It is this dispatchability that we wish to optimize in CSP.

Ancillary services such as spinning reserves can provide grid reliability and contribute to profitability of an energy resource. We exercise an existing dispatch optimization model to estimate the profitability of a concentrating solar power plant (CSP). In this model, we incorporate the sale of spinning reserves in the ancillary service market. We use the National Renewable Energy Laboratory's (NREL) Sytems Advisor Model (SAM) to simulate the workings of a CSP plant within a 72-hour rolling horizon framework. Assuming a price-taker approach with price data from the California Independent System Operator (CAISO) and Electricity Reliability Council of Texas (ERCOT), we find that selling spinning reserves in addition to electric energy increases profits of a CSP plant by up to 7%. This finding suggests that it is viable for a CSP plant with storage to participate in selling spinning reserves, while also contributing to grid reliability and clean energy production.

In our third paper, *The Role of Microgrids in Advancing Energy Equity Through Access and Resilience*, we examine the role of microgrids in advancing energy equity by (i) extending access to electricity in areas where national grids do not reach, and (ii) enhancing a power system's resilience — the ability to adapt to and rebound from unanticipated shocks — in times of disaster(s) such as extreme weather events or power outages on the centralized grid. In the developing world, access to electricity remains a challenge in the most interior rural areas, where incomes are low and grid connection costs are prohibitive. In both developing and developed economies, the rise of extreme weather events has made the resilience of power systems a concern. Wildfires, for example, are becoming widespread. The United States saw over 71,000 wildfires burn 10 million acres and more than 12,000 buildings in 2017 alone. This specific economic burden — in terms of the impact of wildfires on the U.S. economy — is estimated to be between $71.1 billion and $347.8 billion annually. In addition, there is a social cost incurred by vulnerable populations who (i) may be unable to evacuate from the location of a disaster, or (ii) may not have access to mitigating strategies for failed power systems. In this tutorial, we examine the role of microgrids in electricity access and resilience through a systematic review. With respect to electricity access, we investigate the impact of electricity provision through microgrids on outcomes in rural areas of developing countries. For electricity resilience, we assess the effectiveness of microgrids in providing support to power grids in the aftermath of a disaster. We find that microgrids can provide significant benefits in both settings.

CHAPTER 2

DOES UNIVERSAL ELECTRIFICATION SHIELD FIRMS FROM PRODUCTIVITY LOSS?

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Abstract

Universal electrification may be a necessary but not sufficient condition for reliable electricity supply. Yet countries that have achieved universal electrification have made significant investments in building reliable electricity infrastructure relative to countries with low electrification rates. We examine the relationship between power outages and firm performance in four middle-income countries with universal electrification. Using data from the World Bank Enterprise Survey on over $8,000$ firms from 39 regions across Egypt, Morocco, Tunisia, and Indonesia, we find no discernable negative association between outages and firm performance in two of three different specifications we employ. There is also some cross-country heterogeneity; we find some negative association between outages and firm performance for firms in Tunisia from our main specification with total annual sales as explained variable. However, these results for firms in Tunisia are not robust to other specifications with value added and total factor productivity as explained variable. Overall, our results are mixed, showing either a nonexistent or weak negative relationship between power outages and firm performance. These findings suggest that universal electrification is an important development goal, and while universally electrified countries may suffer some outages, firms in these countries are able to adapt to the remaining problems of reliability without incurring significant productivity losses.

2.1 Introduction

There is a well-established body of literature documenting positive impacts of electrification rollout on rural employment, firm productivity and other development outcomes. In these studies, electrification is used to imply an investment in electrical and grid infrastructure that increases the pool of people, households, and firms that are connected to the grid. However, the literature on the impact of electrification is now mixed. Findings from more recent studies using experimental designs have called into question long-standing, positive impact found in earlier studies [Lee et al., 2020, Bayer et al., 2020]. In these earlier studies, electrification has been shown to improve female employment in rural South Africa [Dinkelman, 2011], and the Human Development Index and living standards in Brazil [Lipscomb et al.,

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2013], to name just a few examples. Yet, a replication of Lipscomb et al. [2013], a work which relies heavily on geography for identification, asserts that there are inconsistencies in the definition of geographical areas used throughout the study [Bensch et al., 2021]. Similarly, Bensch et al. [2021] argue in a another replication of Dinkelman [2011] that the exclusion restriction — a central requirement which drives the validity of the instrumental variable — is not satisfied.

In this study, we focus on the relationship between power outages on firm performance in countries with universal electrification. Universal electrification refers to a 100 percent rate of electrification in any country of interest, where access to electricity has reached both urban and even sparsely populated rural areas, and all households and firms are connected to the grid. Power outages are a common feature of life in many developing countries and often result from poorly managed utilities, low generation capacity, rising electricity demand, and even lower distributed power due to aging transmission and grid infrastructure. Evidence from extant literature on the effects of power outages suggests that firms suffer a reduction in productivity and revenue, even if modest. Allcott et al. [2016], for example, estimate that outages in India reduce average plant revenue and producer's surplus by 5 to 10 percent; average productivity losses are estimated to be significantly smaller. Extant literature has focused mostly on the impact of power outages within the context of persistent outages — where universal electrification is yet to be achieved.

The African Development Bank and United Nations have set ambitious targets for attaining universal electrification by 2025 and 2030, respectively. Other development-oriented institutions have articulated similar targets.[2] This emphasis on universal electrification largely ignores concerns about reliability. Nevertheless, universal electrification does not necessarily imply a reliable or readily high quality of electricity supply to industry. Therefore, firms in countries with universal electrification may well find the quality of electricity supply to be an obstacle affecting productivity. While persistent outages are a common feature in sub-Saharan Africa;[3] by contrast, in all four countries in this study, the number of firms experiencing outages in a given year is below 30 percent (see Figure 2.1). But even so, many of these firms have reported power outages as a part of the obstacles they face, as shown in Figure 2.2. Yet, outages, otherwise referred to as electricity, in firms' ranking of obstacles do not rank in the top five of the biggest obstacles to business operations in these countries according to survey responses provided by firms. Figure 2.5 shows a ranking of the biggest obstacles to business operations in the full sample of all firms. Ayaburi et al. [2020] define a metric to measure "reasonable reliability" as fewer than 12 outages in a year. While all four countries in this study have reached a 100 percent rate of electrification, average power

[2]The DFID Energy Africa campaign launched a campaign to achieve universal access to electricity by 2030 including through the deployment of off-grid solutions.

[3]In certain sub-Saharan African countries, over 50 percent of firms experience outages, and the worst-hit firms experience up to 100 hours of power outage per month. This figure is computed from WBES data on a select sub-Saharan African countries.

outages monthly are between 2 and 3 for affected firms.[4] This amounts to over twenty outages per year, and raises a concern about reliability. However, only a relatively small subset of firms experience outages, and it is possible that affected firms may be able to adapt to outages such that their productivity is not impacted.

We use a repeated cross-sectional dataset containing $8,348$ firms from the World Bank Enterprise Survey to estimate the relationship between outages and firm performance. Our dataset which is collected using a stratified random sampling approach covers three different sizes of firms — small, medium and large. Sectors are broadly classified into manufacturing and retail, but we use the two-digit standard industrial classification (SIC) dummies in our regressions. Surveys are generally prone to errors of recall which can result in attenuation bias in our estimates. We discuss our approach to alleviating this problem in Section 2.4. Firm performance is measured using the logarithm of value-added and total annual sales — the two outcome variables of interest. Following Hjort and Poulsen [2019], value-added is computed as total sales revenue less the cost of raw materials and intermediate input. We also compute total factor productivity (TFP) as a residual from industry-specific ordinary least squares (OLS) regression of the logarithm of sales on the logarithm of labor and material inputs.[5] We use both a dummy variable — whether a firm experiences outage or not (Outages Dummy) — and the total number of outage hours (Outage Hours) as a measure of reliability. Assessing the impact of infrastructure on growth and development outcomes is fraught with endogeneity. Outages are usually not exogenous to firm productivity. Weak institutions at the national or regional level could impact both outages and firm performance, and investments in critical infrastructure such as roads and transportation systems may be concentrated in certain localities. Such investments are likely to boost productivity in localities where they are made while also affecting reliability of power supply. Instrumental variables have been employed to address these concerns in many electrification studies. Yet, satisfying the exclusion restriction is often an uphill task when studying the placement of infrastructure, even with the most carefully constructed instruments. Further, instrumental variables are unable to address the problem of self-selection in which firms locate in regions or cities with favorable economic or power supply arrangements. Consequently, studying the impact of outages in countries where outages are a function of economic or political conditions presents several challenges. Put differently, absent random assignment of outages as in Abeberese et al. [2021], in which an electricity rationing program was exploited to generate exogenous variation in exposure

[4] Average monthly outages for affected firms in each of the four countries are calculated from the WBES dataset.

[5] While TFP measures from Olley-Pakes [Olley and Pakes, 1992], Levinson-Petrin [Petrin et al., 2004] and Wooldridge [Wooldridge, 2009] are commonly used in the literature, the lack of panel data prevent the use of these methods. More so, our data set does not include information on the capital stock of firms, so we include material input as a proxy for capital stock, hence our measure of TFP is arguably not the most reliable. As a result, we use sales in the main specification, and TFP for robustness checks.

to outages, estimating the causal impact of outages remains intricate. While we can not claim that outages are completely random in the countries we study, we estimate the relationship between outages and productivity in these countries using OLS with fixed effects while controlling for firm and city level effects as our main specification. For comparison with our OLS estimates only, we construct an instrumental variable,[6] which although satisfies the relevance requirement fails to met the exclusion requirement. Consequently, our estimates likely feature some biases due to the endogeneity concerns mentioned earlier.

The results of the relationship that we estimate are nuanced and mixed. We find no significant relationship between outages and firm performance in the total sample of 8,348 firms across all four countries from our main specification. Similarly, the results across generator ownership category mirror that of the full sample of all firms, i.e., in the full sample, outages have no negative association with firm performance regardless of whether firms own a generator or not. When we disaggregate across countries and generator ownership in each of the countries, results from our main OLS specification show that firms experiencing outages in Tunisia may be more susceptible to loss in sales. While the outages dummy measure suggests that experiencing outages is associated with an 11 percent reduction in total sales, we do not find statistically significant association using the outage hours measure. However, when we use TFP as measure of firm performance we fail to find a significant relationship between outages and firm performance using both outages measures for firms in Tunisia. Similarly, we find no statistically significant evidence of the outage measures when we use valueadded as the explained variable. For firms in the other three countries, we equally find no evidence of a significant negative association between outages and firm performance, although the coefficient on both measures of reliability are mostly negative for all the countries. Contrastingly, in the same specification with TFP as explained variable, we find a minuscule yet statistically significant relationship between the outage hours variable and firm performance. However, this relationship is not repeated in the other specifications.

The main contributions of this paper are, therefore: First, to establish that firms, even in settings with universal electrification, self-report that power outages are an obstacle to performance, even if reliability is relatively higher for these firms than for those in sub-Saharan Africa. Second and most importantly, investigating the impact of outages on performance of these firms provides useful knowledge about the extent to which reliability is a problem even for firms where universal electrification prevails. We find the results across the countries ranging from null to mixed. But an important question arises here: why should

[6]We employ as an instrument for the discrete measure of outage — outages dummy — for firm i, a measure of average outages for firms other than firm i in the same region. In a similar fashion, yearly outages of firm i is instrumented by a measure of average yearly outages for firms other than firm i in the same region. Our instruments, while correlated with the endogenous variables, may not directly affect firm performance once we condition on firm-level and city-level controls. Unobserved time-invariant regional and industry-level effects are accounted for by region and industry fixed effects. However, confounders affecting the endogenous variable are likely baked into the instrument as well since it is computed as an average.

the potential impacts of power outages be any different for firms operating under conditions of universal electrification, for a given outage frequency? One reason is that in countries with universal electrification, only a small percentage of firms invest in generators. The total percentage of firms in Morocco that own a generator for example is about 10; it is about the same for the other countries except for Indonesia with over 20 percent of firms owning a generator as shown in Figure 2.3. This could mean, on one hand, that for most firms, the disruption caused by outages is not severe enough to justify owning a generator.[7] Hence, firm performance may not be significantly impacted by occasional outages. On the other hand, the low percentage of generator ownership could mean that most firms cannot afford to own a generator even though their productivity[8] is impacted by outages. Our results suggest that these countervailing explanations of generator ownership differ across countries. Finally, estimating the relationship between outages and firm productivity also helps us understand if productivity across firms operating under conditions of universal electrification differs significantly in the wake of outages affecting only a subset of these firms.

The rest of this paper is organized as follows: Section 2.2 examines more extensively the literature on electrification and its impact on firm productivity and other development outcomes. Section 2.3 provides a succinct background on the state of the electrification in each of the four countries. Section 2.4 details source of data and empirical approach. Results are discussed in Section 2.5, while 2.6 covers extension and robustness checks. Section 2.7 concludes.

2.2 Literature Review

There is scant literature to date on the impact of power outages on firm performance under conditions of universal electrification. Alby et al. [2011] study reliability of electricity supply in 87 developing countries, including countries in North Africa and Southeast Asia. However, they focus on the link between electricity reliability and firms' decisions to invest in self-generation. Countries with high rates of electrification, approximately 100 percent, have reached a milestone that developing countries aim for; hence, the vast majority of research on the subject focuses on countries where power outage is endemic. This overwhelming focus on countries suffering more frequent outages seems to presuppose that outages in high-electrification countries are not of significant interest. The studies reviewed here are among the body of work examining the effect of power outage on various measures of firm performance in developing countries with varying rates of electrification.

[7] According to data from the World Bank Enterprise Survey, the percentage of firms that own or share a generator in the sub-Saharan Africa region is significantly higher than that of firms in the countries profiled in this study.
[8] We use firm productivity interchangeably with firm performance.

An appreciable number of studies have examined the impact of electricity supply reliability on households' decisions to connect — Buenestado et al. [2020] and Millien — and on firms' performance and revenues Allcott et al. [2016], Cole et al. [2018], Fisher-Vanden et al. [2015] and Alam [2013]; job creation potential Mensah [2018]; economic growth and industrial development Andersen and Dalgaard [2013], Kassem [2021]. Identifying the effect of infrastructure on growth and development outcomes is often empirically challenging since both development and the placement of infrastructure tend to occur simultaneously in developing countries. However, a range of studies in the development literature have made progress in this area through the application of instrumental variables (IV) strategy. Duflo and Pande [2007] and Banerjee et al. [2012]. But even so, finding or devising a completely exogenous instrument is often an exacting task. As Briggs [2021] argues, other than economic and technical factors, politics is also critical in project placements or resource allocation. Therefore, IV strategies that rely on infrastructure as an instrument may still have to contend with potential correlation between the instrument and other confounders.

Fisher-Vanden et al. [2015] find that in response to electricity outages, per unit cost of production increased by 8% across all industries in China, consisting of 23,000 Chinese firms within the study period. The ability of the firms to re-optimize by buying intermediate goods rather than producing them in-house in the wake of outages averts substantial productivity losses. Allcott et al. [2016] estimate that due to power outages, Indian manufacturers suffer a mere 1.5% loss in productivity, although revenues reduce by a greater percentage. Fried and Lagakos [2020], in a departure from empirical modelling, build a dynamic macroeconomic model to analytically show how power outages affect firm productivity in sub-Saharan Africa. They argue that empirical models describe only short-run partial equilibrium effects, which may be modest. However, longrun general-equilibrium effects from their analytical model include an increase in productivity per worker from eradicating power outages. They conclude, therefore, that engineering policies to tackle outages is a worthwhile goal. While most of these studies examine the causal effect of power outage in countries where outages are widespread, this paper attempts to identify the effect of outages on firm performance within the context of universal electrification. The findings from the cited studies vary in magnitude of effect, and relate to different outcome variables, but there is a common theme: unreliable power supply reduces firm productivity, even if modestly in some countries.

This paper resembles Allcott et al. [2016] and Cole et al. [2018] in spirit, in that it studies how firms' performance is impacted by outages, even if under different operating conditions. Allcott et al. [2016] adopt change in the supply of electricity from hydropower production as an instrument. They submit that the effect of power outage depends on firm characteristics, where firms with back-up generators suffer increased production costs while firms without generators may need to temporarily delay production, in turn, incurring more productivity losses. Another study on Indian firms finds that the effect of power shortage varies across industries. While some firms possess the capacity to re-optimize in the wake of power outage, others — mostly electricity-intensive industries — are inevitably hard hit, and suffer productivity losses [Alam, 2013]. In a similar study of Ghanaian firms, Abeberese et al. [2021] argues that due to rationing of power supply in Ghana, outages can be viewed as arguably random; thus, they estimate the effect of outages on firm productivity using a fixed effects model. Their findings show that among small Ghanaian firms, outages result in a 10% loss in productivity. Adenikinju [2005] similarly finds that in Nigeria, small-sized firms are most impacted by power outages.

Work in the electrification literature has focused on the problem of power outage where a sizable number of firms list power outage as a major problem. However, there is a considerable gap in knowledge regarding the effects of power outage where only a relatively smaller percentage of firms list electricity as an obstacle, and outage frequencies are lower. This paper fills that gap in knowledge. In order to understand some of the mechanisms through which productivity losses occur, this paper also disaggregates firms into two categories: generator ownership — firms that own a generator, and no generator — firms that do not own a generator. The main objective is to assess the extent to which firms suffer losses in productivity when they experience power outages. Understanding the relationship between outages and firm performance in these countries can provide a basis for comparison with firms for which electrification rates are lower, and outages are more frequent.

2.3 Background

Electrification rates have since reached a 100% in the countries we study with the exception of Indonesia, where it reached 99% in 2019. Among these four countries, Egypt and Tunisia attained universal electrification in 2016. However, in Egypt, outages became more prevalent in 2014 as a result of unmet rising demand and low investments in infrastructure and power stations. The outages were particularly severe between 2011 in 2014 following political uprising, averaging six power cuts a day for up to two hours at a time at its peak.[9] The key challenges of the power sector in Egypt include very high subsidies and poor maintenance of power infrastructure [Rana and Khanna, 2020].

According to responses by firms in Tunisia, electricity is considered less of an obstacle, ranking at 12^{th} place among the 15 biggest obstacles identified by firms. Unlike Egypt, news of power outages in Tunisia are not as common in the media. Other than the infamous major outage that hit most parts the country in August 2014, outages have been infrequent and restricted to certain localities at different times [Kilani et al., 2019].

[9] `https://www.theguardian.com/world/2014/aug/20/egypt-blackouts-energy-crisis-power-cuts`

Morocco implemented a sweeping power reform in the 90s which introduced private sector participation for generation capacity expansion and electricity distribution. Following this reform, the country experienced a massive growth in electrification from less than 60% in the 90s to over 90% by mid 2000s. Rural electrification also soared from a paltry 15% in 1995 to nearly a 100% in 2017. Yet, challenges stemming from reliance on electricity exports and unsustainable tariff from the country's utility persists [Usman and Amegroud, 2019].

Finally, in Indonesia, the state electric utility, Perusahaan Listrik Negara (PLN), went through a transition period that rendered it bankrupt and bereft of competent personnel leading to mismanagement of the utility. This situation resulted in rationing of electricity supply to households and business. However in the 90s, following a rapid expansion of transmission grid in parts of the country, supported by massive national investments, the country experienced a surge in electrification rate, which lead to a significant decrease in reliance on back-up generators particularly for manufacturing firms [Kassem, 2021].

2.4 Empirical Approach

This paper estimates the relationship between outages and firm performance across four middle-income countries. The ideal dataset for investigating this relationship is a large dataset that comprises different categories of firms in these countries, and is nationally representative. Such a dataset will also cover information on a wide range of firm attitudes, challenges and performance indicators. Additionally, details such as the community-level location of firms is important for grouping firms at a more granular level because certain firm and community characteristics may differ at the community rather than regional level. We use cross-sectional data from the World Bank Enterprise Survey (WBES). The survey originally covers $8,348$ firms in 39 different regions across four countries. Survey years span 2013 to 2020. However, the WBES dataset does not provide the community-level locations of firms, so we group firms at the regional level. Table Table 5.1 provides the summary statistics of the key variables used in this paper.

The WBES is a nationally representative survey, which provides information on firms' attitudes, attributes, access to infrastructure, and obstacles that firms face in the day-today running of business. The survey adopts a two-stage stratified random sampling strategy. Top managers and business owners in 139 countries are interviewed face-to-face to gather this information. The countries in this study were selected because they are middle-income countries that have achieved universal electrification, and have a sufficiently large sample of firms that both responded to the WBES survey and answered questions related to the reliability of electricity supply. The measures of firm performance that we use in this study are the logarithm of total annual sales and the logarithm of value added and total factor productivity. All monetary variables are deflated to 2010 levels using a GDP deflator from the World Bank development indicators database and then transformed into US dollar values using the Purchasing Power Parity (PPP) Index from the International Monetary Fund. The explanatory variable of interest is outages, which is measured as both a dummy variable — whether a firm experienced an outage or not — and the total hours of outages in a month. Other control variables include the total number of workers employed, managers' years of experience, age of firm and access to finance. These control variables are important covariates. For instance, the strength of the workforce and level of experience of a manager often have an impact on overall firm performance. Other dummy variables include generator ownership, government ownership, foreign ownership, size of firms, and city size. While generator ownership affects how a firm responds to outages, the level of government and foreign stake in a firm may indirectly affect productivity. We also control for access to finance which plays an important role in the ability of firms to expand production activities.

The variables in this study are constructed mostly from self-reported figures, and are thus prone to the usual errors associated with self-reporting. Such self-reported figures also result in the creation of outliers. To reduce the impact of outliers, we log-transform values of all variables, and return as missing those values that are three standard deviations away from the mean.[10] Firms in this study are of three sizes: small, medium and large. Large firms, which constitute 22 percent of all firms in our sample, have over 100 employees, while medium (between 20 and 100 employees) and small firms (less than 20 employees) constitute 29 and 49 percent of all firms, respectively. Out of the total $8,348$ firms in the sample, $4,592$ are in Egypt, $1,452$ in Morocco, $1,203$ in Indonesia, and $1,101$ in Tunisia. On the broad categorization by industries, 63 percent of all firms in the sample are manufacturers, while all others are service firms. Egypt has the highest average number of yearly outages, and the highest percentage of firms experiencing outages, followed by Tunisia and Morocco. Indonesia has both the lowest number of yearly outages and the percentage of firms experiencing outages. Unlike firms in sub-Saharan Africa, firms in this study do not suffer as acute power outages. Calculated average number of power outage for affected firms in our study is about 117[11] hours per year, whereas in some countries in sub-Saharan Africa, firms face more than 500 hours of outage per year.[12] Over 4,000 firms claimed that electricity represents some level of obstacle to their productivity in these countries. However, it is curious that many of the firms that cite electricity as an obstacle reported not to have experienced outages in the past financial year.[13] Moreover, as shown in Figure 2.13 through Figure 2.16 in the Appendix, electricity does not rank in the top five obstacles

[10] The log-transformation is performed only to remove outliers, but control variables are not logged in the regressions. This follows the recommendations of the Enterprise Analysis Unit of the World Bank. See `https://www.enterprisesurveys.org/en/methodology`

[11] This figure is calculated from the WBES dataset as average number of monthly outages multiplied by average total duration of outage.

[12] In a study of the impact of power outages on firm performance in sub-Saharan Africa, Cole et al. [2018] estimate that 8 countries out of the 14 they examine face on average more than 500 hours of outages each year.

[13] The total number of firms that claimed to have experienced outages in the year preceding the survey is 2243.

enumerated by firms in any of these countries. Indonesian and Tunisian firms in particular rank electricity very low in the list of obstacles they face. Also, the percentage of firms that own or share a generator is low compared to the sub-Saharan average.[14] The average number of firms that own or share a generator is only 14 percent in our sample.

2.4.1 Empirical Approach — OLS

If the incidence of power outages experienced by firms were randomly assigned, the effect on performance outcomes can be estimated using a simple ordinary least squares (OLS) method. However, the occurrence of outages as experienced by some firms is likely to be influenced by a range of factors. For example, the location of firms may determine whether they experience an outage or not. Moreover, high productivity, high revenue-generating firms may self-select into regions where power outages are typically non-existent, while firms that are not as productive may be clustered in regions where outages are pervasive. This selection effect is likely to bias any OLS estimate comparing firms on the basis of outages experienced.

Another source of endogeneity that can result in biased estimates is the influence of unobserved factors that are correlated with outages and firm performance. Political institutions and socioeconomic factors can influence both the occurrence of outages and the outcome variable of interest. If this were the case, it can be argued that results generated from an OLS regression may be partly driven by these unobservable factors, rather than by outages only. Specifically, other firm-level unobserved characteristics such as access to other infrastructure like proximity to road transport can result in a positive bias as firms with access to this infrastructure are likely to experience fewer outages, thereby creating a positive correlation between access to other infrastructure and the explanatory variable of interest. The bias could also be negative for firms with lower access to referenced infrastructure.

Finally, self-reported measure of outages is likely to contain some margins of error, which can result in attenuation bias in an OLS estimate. Our main specification is an OLS regression which examines the relationship between power outages on an outcome variable of interest — sales, controlling for both firm-and city-level characteristics. Industry, regional and country fixed effects are also applied where applicable. It is specified as follows:

$$\mathrm{Y}_i = \beta_0 + \beta_1 Outage + \mathbf{X}_i^{'}\beta_2 + \delta_j + \lambda_r + \phi_t + \varepsilon_i \tag{2.1}$$

where Y_i is the outcome variable of interest at firm i. Outage represents both a dummy variable, indicating whether a firm experiences outage or not, and the total outage hours measure. The observable firm-level

[14] Cole et al. [2018] estimate that the continental average of generator ownership, using 14 countries in sub-Saharan Africa is 52%.

characteristics, $\mathbf{X}_i^{'}$, include top manger's years of experience, total number of workers, age of firm, generator-ownership, government ownership, foreign ownership, access to finance, size of firm and city size. Industry fixed effects which capture time-invariant factors that are common across firms within an industry are represented by δ_j, while λ_r represents district/region fixed effects and ϕ_t is year fixed effects. The error term is represented by ε_i. This simple specification provides a straightforward way to estimate β_1. The estimated coefficient of β_1 represents the extent of association between outages and firm performance. While this specification can provide an estimate of the relationship between outages and firm performance, macroeconomic conditions such as economic growth or decline, and a dynamic political climate can confound the relationship between the outcome and explanatory variables of interests. OLS estimates from this specification are at best indicative of the direction of the relationship between outages and firm performance. Given that the omitted variables in this specification are likely to be negatively correlated with outages but positively correlated with firm performance, we expect estimates from this specification to be negatively biased. Another endogeneity concern is that some firms may locate in regions where outages are infrequent. While we are unable to address this concern directly, we find that in all the 39 regions, there is not a single region where firms do not suffer outages. There are only five regions where more than 90% of all firms did not experience outages in the past year, and only one region with more than 95% of all firms which did not experience outages.[15] This absence of a particularly high degree of concentration of firms that did not experience outages in many regions relieves some concerns of endogeneity resulting from firm placement. To alleviate any remaining concern, we employ city-level controls, which addresses issues of wealth or income differences across different city sizes.[16]

2.4.2 Instrumental Variables

In this section we discuss possible ways to address endogeneity concerns and potential challenges that may arise. Instrumental variables have been applied widely to estimate the impact of outages or the placement of electricity infrastructure on firm performance and other development outcomes. [Lipscomb et al., 2013, Allcott et al., 2016, Cole et al., 2018] Yet these studies are not without flaws, most notably the validity of the instrument in satisfying the exclusion restriction. We construct a simple instrument not as a main specification but to aid in the comparison of the results with those from our main OLS specification. The IV approach entails estimating a two-stage model, defined as follows:

[15] Note that the total percentage of all firms that did not experience outage in the year preceding survey year is 73. Similarly, there are only five regions in total where the concentration of firms with outages in past year exceeded 50 percent.

[16] Cities are classified into four classes according to the population of the cities: Bigger cities, with a population of above 5 million people, big cities with a population of between 2 and 5 million, medium cities with population below 2 million people, and small cities with population below 500,00 people.

$$\mathrm{Y}_i = \alpha_0 + Outage_i\alpha_1 + \mathbf{X}_i^{'}\alpha_2 + \delta_j + \lambda_r + \phi_t + \mu_i \tag{2.2}$$

$$Outage_i = \beta_0 + \mathbf{Z}_i\beta_1 + \mathbf{X}_i^{'}\beta_2 + \delta_j + \lambda_r + \phi_t + \varepsilon_i \tag{2.3}$$

In both equations, $\mathbf{X}_i^{'}$ includes the full set of controls as listed above. Instrument $\mathbf{Z}_i$ represents both instruments for the outage dummy and yearly outage measure is computed as (i) the average of outages dummy for firms other than firm i in district r and (ii) as the average of total outage hours for firms other than firm i in district r:

$$\mathbf{Z}_i = \frac{\sum_{i'} Outages_{i'r}}{n_i} \tag{2.4}$$

where $Outages_{i'}$ is dummy (or yearly outages) for all firms other than firm i in region r, and n_i is total number of firms in region r. Identification of the IV model requires, first, a strong correlation between the outages measure and the instruments, $\mathbf{Z}_i$, i.e., the condition that $Cov\ (z,\ Outage) \neq 0$ must be satisfied. This requirement is well satisfied. The results of our first-stage regression in Table Table 2.2 shows a strong correlation between the endogenous variable and the instruments. First-stage F-statistics reported in the IV results in Table 2.10 through Table 2.12 Appendix A are also large enough to avoid weak instruments concerns in most specifications. Secondly, the exclusion restriction, $Cov\ (z, \varepsilon) = 0$ implies that the instruments need to be as good as randomly assigned. More so, the effect of the instruments on the outcome variables should be mediated fully, and only through the endogenous variable. Outages experienced by firm i are correlated with outages experienced by other firms in the same region as firm i. While a more granular geographical level such as a community would have provided an even tighter correlation, our dataset does not provide that granular community-level location of firms. Our identifying assumption should rely on one hand, on the strong correlation between outages and our instruments. On the other hand, the instruments — outages of firms other than firm i in a given region — should not affect the productivity of firm i directly, particularly after controlling for other firm and region characteristics.

Spatial instruments such as the one we employ here have been roundly criticized in the literature for their inability to produce valid inference. Specifically, Betz et al. [2018] caution that if these instruments are strong, they are likely to violate the exclusion restriction, and if they do meet the restriction, they are likely to be irrelevant. To make valid inferences, we require our instruments in this case, i.e., the average outages of firms other than firm i, to impact the productivity of firm i only through the outages of firm i. However, this condition is easily violated as the same unobservable factors that confound the relationship between the outages of firm i and its productivity are plausibly present in the average outages of firms other than firm i. In other words, firms in the same region typical face the similar economic and socio-political environment, hence the outages experienced by firms other than firm i are partly a function the same environment. This violation casts doubt on the validity of our instruments and the results thereof. However, we sample results from this specification in the full sample of all firms for comparison with the OLS estimates, and present country-specific results from the IV in Table 2.10 through Table 2.12 of Appendix 2.8.

Table 2.1 Summary Statistics

Variable	Obs.	Mean	Std. Dev	Min	Max
Sales	8,348	118,330.96	970,823.52	8.681	54,663,416
Log Sales	8,348	8.883	2.221	2.161	17.817
Past Sales	8,348	105,304.03	2,033,180.1	0	173,600,000
Log Past Sales	7,788	8.653	2.253	.406	18.972
Value Added	4988	104,894.43	107,6319.7	0	53,848,436
Log Value Added	4,973	1.106	1.255	0.0387	66.60144
TFP	4,939	1.106	1.255	0.038	66.601
Yearly Outages	8,348	8.576	23.972	0	300
Outage Hours	8,348	2.035	13.208	0	360
Manager's Experience	8,164	20.941	11.277	1	70
Permanent Workers	8,333	112.613	346.996	1	8,500
Age of Firm	8,348	58.687	256.068	3	2,030
Outages	8,348	.269	.443	0	1
Finance Access	8,209	.652	.476	0	1
Generator Ownership	8,348	.138	.344	0	1
Foreign Ownership	8,179	5.267	19.210	0	100
Size of Firms	Frequency		Percent		Cummulative
Small	4,079		49.08		49.08
Medium	2,392		28.65		77.73
Large	1,859		22.27		100
Total	8,348		100.00		
Size of Locality	Frequency		Percent		Cummulative
Bigger City	1,386		16.60		16.60
Big City	3,826		45.83		62.43
Medium City	1,600		19.97		81.60
Small City	1,536		18.4		100
Total	8,348		100.00		

Notes: This table provides summary statistics of all key variables in this paper. Sales value are expressed in purchasing power parity 2010 dollars. Our regression tables omit Small City in the city-size categories and Large Firms in the firm-size category in order to serve as the reference group.

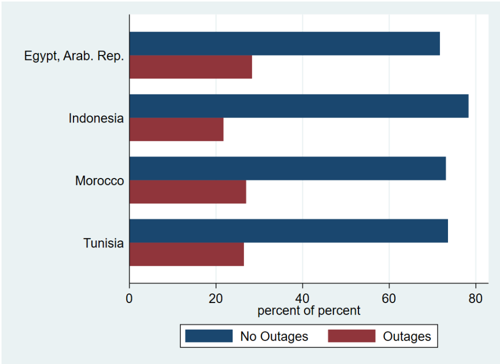

Figure 2.1 This figure shows the percentage of firms in each country that reported experiencing outages in the year preceding the survey. The percentage of firms that experienced outages is shown in red, while the percentage of firms that did not experience an outage is shown in blue.

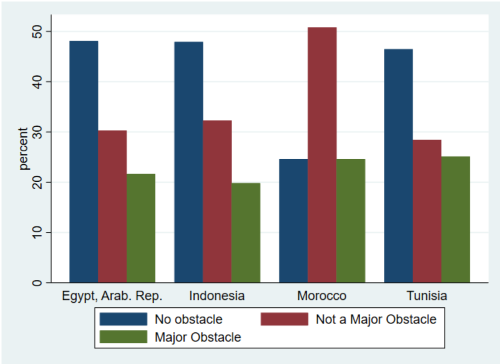

Figure 2.2 This figure shows the level of obstacle that electricity represents for all firms in each of country. This is a self-reported measure of how firms perceive power outages to be a hindrance to their operations. Originally, there are five categories of obstacle levels: no obstacle, minor obstacle, moderate obstacle, major obstacle and very severe obstacle. We collapse minor and moderate obstacle to Not a Major Obstacle (red), major and very severe obstacle to Major Obstacle (green). No Obstacle (blue) remains unchanged.

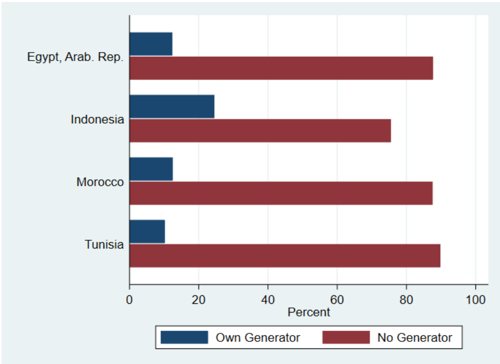

Figure 2.3 This figure shows the percentage of firms that own or share a generator in comparison with those that do not in all four countries. The percentage of firms that own a generator is shown in blue, while the percentage of firms that do not own or share a generator is shown in red.

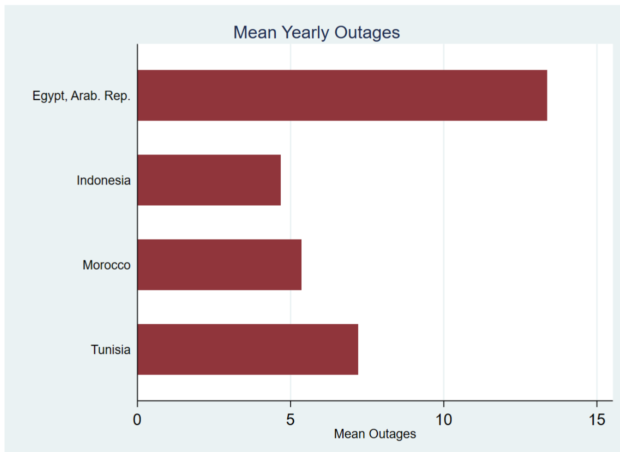

Figure 2.4 This figure shows the average number yearly outages experienced by the firms in each of the four countries. This number is calculated as the mean of total number of yearly outages among all the firms in each of the four countries. Egypt has the highest number, followed by Tunisia, while Indonesia has the lowest number of average yearly outages.

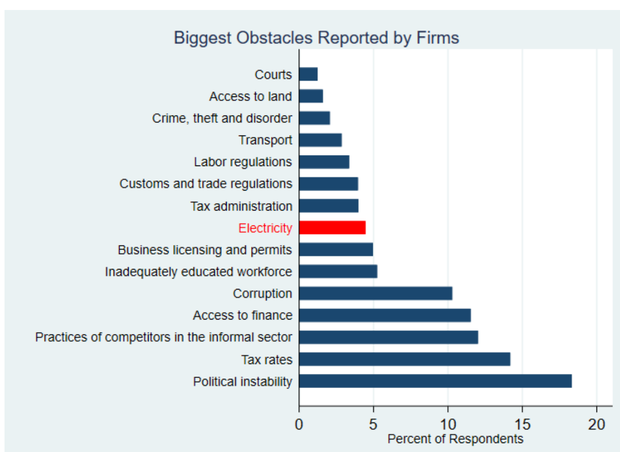

Figure 2.5 This figure shows the self-ranking of the biggest obstacles faced by firms across all four countries. Political instability is ranked as the biggest obstacle while electricity, marked in red, is ranked 8^{th} amid the 15 obstacles identified from firms responses. The ranking of the these obstacles differ slightly across the countries.

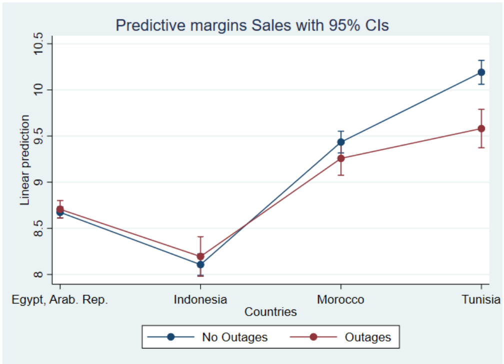

Figure 2.6 This figure shows the predicted average sales with 95% confidence intervals for both firms that experienced outages (red line) and those that do not (blue line) across the four different countries we study. Noticeably, the difference in average revenue is more pronounced for firms in Tunisia. The figure comes from linear regressions of sales on outages and a set of control variables.

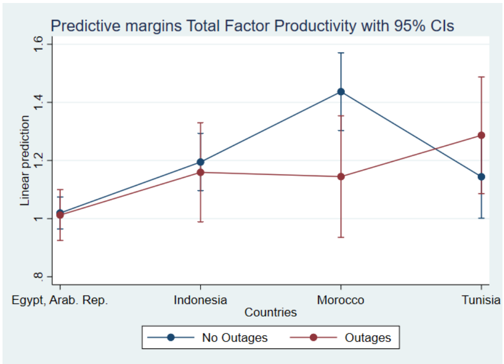

Figure 2.7 This figure shows the predicted average total factor productivity with 95% confidence intervals for both firms that experienced outages (red line) and those that do not (blue line) across the four different countries we study. Noticeably, the difference in average revenue is more pronounced for firms in Tunisia. The figure comes from linear regressions of total factor productivity on outages and a set of control variables.

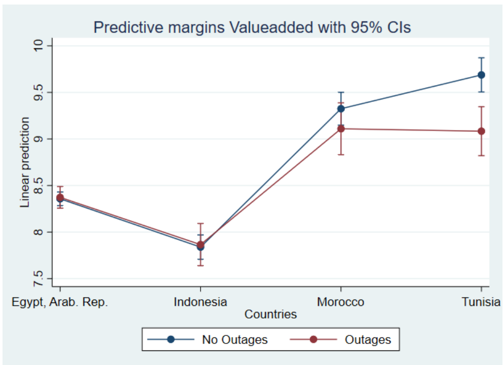

Figure 2.8 This figure shows the predicted average total factor productivity with 95% confidence intervals for both firms that experienced outages (red line) and those that do not (blue line) across the four different countries we study. Again, the difference in average valueadded is more pronounced for firms in Tunisia. The figure comes from linear regressions of valueadded on outages and a set of control variables.

Table 2.2 Effects of Power Outage on Logged Sales and Logged Value Added for All Firms in the Full Sample

	ln Sales				ln Value Added			
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Outage Hours	−0.000	−0.002			−0.002	−0.003		
	(0.001)	(0.001)			(0.002)	(0.002)		
Outages Dummy (0/1)			0.018	-0.006			0.013	0.052
			(0.055)	(0.078)			(0.054)	(0.081)
Manager's Experience	0.015^{***}	0.015^{***}	0.015^{***}	0.015^{***}	0.011^{**}	0.011^{**}	0.010^{*}	0.010^{**}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
No. Permanent Workers	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Generator	0.711^{***}	0.717^{***}	0.707^{***}	0.712^{***}	0.686^{***}	0.687^{***}	0.677^{***}	0.670^{***}
	(0.087)	(0.084)	(0.087)	(0.085)	(0.090)	(0.093)	(0.093)	(0.089)
Small Firm	-2.115^{***}	-2.113^{***}	-2.116^{***}	-2.115^{***}	-2.263^{***}	-2.262^{***}	-2.269^{***}	-2.271^{***}
	(0.116)	(0.113)	(0.115)	(0.113)	(0.115)	(0.112)	(0.116)	(0.113)
Medium Firm	-1.169^{***}	-1.168^{***}	-1.170^{***}	-1.169^{***}	-1.268^{***}	-1.268^{***}	-1.271^{***}	-1.273^{***}
	(0.069)	(0.067)	(0.068)	(0.067)	(0.085)	(0.083)	(0.086)	(0.083)
Age of Firm	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Foreign	0.436^{***}	0.438^{***}	0.436^{***}	0.436^{***}	0.673^{***}	0.673^{***}	0.670^{***}	0.671^{***}
	(0.088)	(0.088)	(0.089)	(0.088)	(0.091)	(0.090)	(0.092)	(0.090)
Government	0.068	0.066	0.068	0.068	0.223	0.223	0.227	0.228
	(0.171)	(0.168)	(0.171)	(0.168)	(0.219)	(0.215)	(0.219)	(0.215)
Bigger City	0.230	0.222	0.233	0.229	0.130	0.128	0.138	0.144
	(0.149)	(0.145)	(0.150)	(0.147)	(0.200)	(0.196)	(0.201)	(0.197)
Big City	-0.229^{*}	-0.232^{*}	-0.228^{**}	-0.229^{*}	-0.292^{*}	-0.293^{*}	-0.288^{*}	-0.287^{*}
	(0.128)	(0.124)	(0.128)	(0.126)	(0.165)	(0.160)	(0.167)	(163)
Medium City	−0.036	−0.039	−0.035	−0.037	−0.084	−0.085	−0.082	0.095
	(0.127)	(0.124)	(0.126)	(0.124)	(0.171)	(0.168)	(0.171)	(0.168)
Finance Obstacle	0.080	0.079	0.079	0.080	0.092	0.092	0.094	−0.084
	(0.065)	(0.064)	(0.064)	(0.063)	(0.079)	(0.078)	(0.079)	(0.077)
Observation	8,031	8,031	8,031	8,031	4,848	4,848	4,848	4,848
R-squared	0.473	0.473	0.473	0.473	0.525	0.525	0.525	0.525

Notes: This table shows OLS and IV results for the full sample of firms. Columns 1 – 4 show Logged Sales as a dependent variable, 4 – 8 show Logged Value Added as a dependent variable. Industry and country fixed effects are included in this regression. Robust standard errors are clustered at the 39 different regional levels. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

2.5 Results

Table 2.2 presents results for the full sample of firms from all four countries, with OLS and IV specifications for both logged Sales and logged Value Added as dependent variables. Table 2.3 through Table 2.6 present main specification (OLS) results of logged Sales only as the outcome variable.[17] Table Table 2.3 presents results by generator ownership status and firm size. Table 2.4 presents results by country. Table 2.5 and Table 2.6 present these country-level results separately for firms with and without a generator, for both the outages hours and outages dummy explanatory variables.

2.5.1 Full Sample Results

Table 2.2 shows that we find a negative but statistically insignificant relationship between outage hours and both measures of firm performance. Similarly, we find, on average, no significant relationship using the outages dummy variable. The first two columns of Table 2.3 present OLS and IV results, respectively, for logged Sales with total outage hours as the explanatory variable. Columns 3 and 4 use the outages dummy as the explanatory variable. Columns 4 through 8 repeat this pattern with logged valueadded as the dependent variable. We also present coefficients on the full set of control variables, and while industry, and country fixed effects are included in the regressions their coefficients are not reported. Coefficients on both outage hours and the outages dummy are small in magnitude and not statistically significantly different from zero in all specifications. The control variable coefficients indicate that firms with onsite generators have significantly greater sales and value added than those without, as do foreign-owned firms and those with more managerial experience and more workers. Lastly, firms in the second largest city category have lower sales and value added than firms in the largest city category, and firm size classifications in the data also correspond to sales and value added outcomes.

We also examine how outages affect performance by generator ownership status and firm size categories to determine whether firm performance depends on owning a generator or belonging to a particular size class. Table 2.3 shows OLS estimates for firms from all four countries split into firm size and generator ownership sub-samples. Panel A shows these results with outage hours as the measure of reliability, while Panel B uses the outage dummy as the measure of reliability. We find no significant negative association between outages and firm performance across generator and size categories. Across firm sizes, the signs on the outage hours variable are expectedly negative for small and medium firms. Overall our results in this category, while not statistically significant have the expected sign in most instances. In other words, in the

[17] We use the logarithm of value added as the dependent variable only in the full sample of all firms in all four countries in Table 2.2. Due to missing values of cost of raw materials, there is a significant attrition in the number of firms in each country for which we are able to calculate value added. As a result, we use logarithm of sales as the outcome for country-specific regressions.

full sample of all firms from the four countries and across generator ownership and size category, we find no evidence of a negative association between outages and firm performance. This null finding is mirrored in Panel B of Table 2.3, which shows the results using the outage dummy as the measure of reliability. Table 2.3 suppresses coefficients on all variables except the reliability measures for reasons of space, but full results with control variables are available upon request.

2.5.2 Country-specific Results

The results from the full sample conceal some heterogeneity across countries. We now examine country-specific impacts of outages on firm performance, measured by the logarithm of sales as the dependent variable. Country-level OLS estimates are shown in Table 2.4; coefficients on the full set of controls are suppressed for space. Panel A of Table 2.4 shows the coefficients on outages hours, while panel B shows the coefficients on the outages dummy, for each of the four countries in our sample. From Panel A, we find no evidence of a negative association between outage hours and firm performance in any of the four countries.

In Panel B, we show that the coefficient on the outages dummy is not significantly different from zero for Egypt, Morocco and Indonesia. However, for Tunisia, the coefficient, -0.116, is both negative and statistically significant at the five percent level. We compare this result with that from the IV specification[18] and find a similar association. This result taking on its own suggests that experiencing outages in Tunisia is, on average, associated with an 11% reduction in total annual sales,[20] or 9% according to the IV estimate relative to firms that do not report outages occurring. This is a significantly high amount of loss for this subset of firms. But a careful look at the data and distribution of outages in Tunisia shows that the highest percentage of firms that reported experiencing outages in Tunisia are located in the North west region of Tunisia, the poorest region in the country. In this region, out of a total of 119 firms surveyed, 70, i.e., nearly 60% of firms reported experiencing outages, whereas the average number firms experiencing outages in other regions of the country is just over 20%. We also know that our OLS specification, even after controlling for city effects and population, cannot completely solve the omitted variable bias resulting from an inability to accurately capture the economic and political outlook of the different regions where this firms are located. Such a problem can lead to a negative bias in our estimates. Moreover, this result for firms experiencing outages is not robust to other specifications in our study. Using

[18]The Montiel-Pflueger F-stat for this result is greater only than the 20 percent critical value. Technically, this implies that we can reject the null of weak instrument for our two-stage least square regression for a weak instrument threshold of $\tau^{19} =$ 20%.

[20]This figure was calculated following Halvorsen et al. [1980]. The form of equation estimated in this paper is as follows: $lnY = \alpha + b_i X_i + c_j D_j$. This equation can be written as $Y = (1+g)^D \exp(\alpha + b_i X_i)$. Thus, the coefficient of the dummy variable in first equation is $c = ln(1+g)$. Subsequently, the relative effect on Y is $g = \exp(c) - 1$, while the percentage effect $= 100 \cdot g = 100 \cdot \exp(c) - 1$.

the TFP and valueadded measure, we find no evidence of a negative association between outages and firm performance for firms in Tunisia.

Finally, we also look at country-specific results across generator ownership. These results are shown in Table 2.5 for outages hour, and Table 2.6 for the outages dummy as the explanatory variables, respectively. As before, in Table 2.5, we find no evidence of an association between outage hours and sales except in the case of Tunisia where we find a positive albeit economically insignificant association between outage hours and sales for firms without an onsite generator. This result is counter-intuitive, given that if outages do not negatively impact firm performance, we would expect no positive association at best. But the relationship we see here could be a result of measurement error which is associated with recall bias. Many firms do not keep accurate records of the number of outages the experience or the duration of such outages. More so, many of the firms that claim to have experienced outages have missing data on the duration of these outages. This fact along with the low statistical power that results when country samples are divided into sub-samples are likely to bias our OLS estimate in this case.

In Panel B of Table 2.6, which considers only firms that do not own a generator, we also find that among the four countries, only firms in Tunisia without a generator are affected. Specifically, the coefficient of -0.145 among firms that do not own a generator in Tunisia, indicates that experiencing outages is associated with about 13 percent reduction in total sales. As we pointed out earlier with respect to the results from the full country sample of firms in Table 2.4, this estimate is likely biased as a result of endogeneity stemming from an omitted variable bias problem. For other countries in the generator ownership category, we find no evidence of outages affecting firm performance conditional on owning a generator or not.

2.6 Extensions and Robustness

In this section we report the results of a number of further robustness exercises and extensions. For reasons of space, we do not report coefficients on control variables. Specifically, we use total factor productivity (TFP) and the logarithm of valueadded as the dependent variable and both outage hours and yearly outages as intensity measures of outages as well as the dummy indicator of outages. Due to the attrition[21] resulting from computing total factor productivity, we only estimate the relationship between outages and firm performance using, first, the full sample of all firms across the four countries, and secondly, the full sample for each of the four countries in our dataset. We also disaggregate the full sample of all firms across generator ownership and firm size but do not examine country-specific samples across generator ownership due to the attrition in total number of observation.

[21] The attrition arises from the fact that the WBES dataset contains some missing information on some of the variables used in the computation of total factor productivity

Table 2.3 Effect of Power Outage on Logged Sales, by Generator Ownership Status and Firm Size

	Generator Ownership		Firm Size		
	Generator	No Generator	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)
			Panel A		
Outage Hours	0.002	−0.001	−0.001	−0.002	0.002
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Observation	1,089	6,942	3,508	2,303	1,783
R-squared	0.587	0.447	0.268	0.295	0.371
			Panel B		
Outages Dummy (0/1)	−0.059	0.021	−0.007	0.143	−0.130
	(0.125)	(0.061)	(0.056)	(0.087)	(0.142)
Observation	1,089	6,942	3,508	2,303	1,783
R-squared	0.587	0.447	0.268	0.296	0.371
Firm-Level Controls	Y	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y
Country Fixed Effects	Y	Y	Y	Y	Y

Notes: This table shows OLS estimates for the impact of power outages on firm performance across generator ownership (columns 1 and 2) and firm size categories (columns 3 through 5), for firms in all four countries. Robust standard errors are clustered at the 39 different regional levels in the full sample. The measure of outages in Panel A is Outage Hours, while in Panel B, outages are measured using the Outages Dummy. Both firm-and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, access to finance foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

Table 2.4 Power Outage Effects on Logged Sales by Country

	Morocco	Tunisia	Egypt	Indonesia
	(1)	(2)	(3)	(4)
		Panel A		
Outage Hours	−0.001	0.002	0.003	−0.003
	(0.003)	(0.001)	(0.002)	(0.002)
Observation	1,246	1,081	4,522	1,182
R-squared	0.394	0.739	0.448	0.549
		Panel B		
Outages Dummy (0/1)	−0.094	−0.116**	0.085	0.076
	(0.157)	(0.045)	(0.060)	(0.175)
Observation	1,246	1,081	4,522	1,182
R-squared	0.400	0.547	0.448	0.550
Firm-Level Controls	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y

Notes: This table shows OLS estimates for the impact of power outages on firm performance in each of the four countries (columns 1 through 4). Robust standard errors are clustered at the different regional levels in each country. The measure of outages in Panel A is Outage Hours, while in Panel B, outages are measured using the Outages Dummy. Both firm-and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

Table 2.5 Power Outage Effects on Logged Sales by Generator Ownership Category in Each Country

	Morocco Generator (1)	Tunisia Generator (2)	Egypt Generator (3)	Indonesia Generator (4)
		Panel A		
Outage Hours	0.007	-0.003	0.003	-0.004
	(0.005)	(0.020)	(0.002)	(0.003)
Observation	126	110	561	292
R-squared	0.697	0.726	0.624	0.523
	No Generator	No Generator	No Generator	No Generator
		Panel B		
Outage Hours	-0.001	0.002^{*}	0.006	-0.002
	(0.004)	(0.001)	(0.004)	(0.001)
Observation	1,120	971	3,961	890
R-squared	0.373	0.537	0.405	0.528
Firm-Level Controls	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y

Notes: This table shows OLS estimates for the impact of power outages on firm performance in each of the four countries across generator ownership (columns 1 through 4). Robust standard errors are clustered at the different regional levels in each country. Panel A shows the impact of power outages on firm performance for firms owning a generator, using the Outage Hours measure. Panel B shows the impact of power outages on firm performance for firms without a generator, using the Outage Hours measure. Both firm- and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

Table 2.6 Power Outage Effects on Logged Sales by Generator Ownership Category in Each Country

	Morocco Generator (1)	Tunisia Generator (2)	Egypt Generator (3)	Indonesia Generator (4)
		Panel A		
Ouatges Dummy (0/1)	−0.023	−0.065	−0.052	−0.067
	(0.575)	(0.236)	(0.175)	(0.270)
Observation	126	110	561	292
R-squared	0.695	0.739	0.623	0.521
	No Generator	No Generator	No Generator	No Generator
		Panel B		
Outages Dummy (0/1)	−0.015	−0.145**	0.095	0.035
	(0.176)	(0.045)	(0.082)	(0.163)
Observation	1,120	971	3,961	890
R-squared	0.373	0.538	0.405	0.528
Firm-Level Controls	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y

Notes: This table shows OLS estimates for the impact of power outages on firm performance in each of the four countries across generator ownership (columns 1 through 4). Robust standard errors are clustered at the different regional levels in each country. Panel A shows the impact of power outages on firm performance for firms owning a generator, using the Outages Dummy measure. Panel B shows the impact of power outages on firm performance for firms without a generator, using the Outages Dummy measure. Both firm- and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

Table 2.7 Power Outage Effects on Total Factor Productivity by Country

	All	Morocco	Tunisia	Egypt	Indonesia
	(1)	(2)	(3)	(4)	(5)
			Panel A		
Outage Hours	−0.002**	−0.005	−0.002	−0.000**	−0.002
	(0.001)	(0.003)	(0.001)	(0.000)	(0.002)
Observation	4,819	509	516	2,868	926
R-squared	0.039	0.129	0.282	0.027	0.034
			Panel B		
Outages Dummy (0/1)	−0.040	−0.261	−0.034	−0.008	0.072
	(0.046)	(0.182)	(0.122)	(0.059)	(0.231)
Observation	4,819	509	516	2,868	926
R-squared	0.039	0.465	0.280	0.027	0.034
			Panel C		
Yearly Outages	−0.001	−0.004	−0.002	−0.000	−0.002
	(0.001)	(0.005)	(0.002)	(0.000)	(0.003)
Observation	4,819	509	516	2,868	926
R-squared	0.039	0.128	0.284	0.027	0.034
Firm-Level Controls	Y	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y

Notes: This table shows OLS estimates for the impact of power outages on firm performance in the full sample of all countries (column1) and each of the four countries (columns 2 through 5). Robust standard errors are clustered at the different regional levels in each country. The measure of outages in Panel A is Outage Hours, while in Panel B, outages are measured using the Outages Dummy. Panel C uses the Yearly Outage measure. Both firm-and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, access to finance, foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

Our results from this extension shown in Table 2.7 differ slightly from those of Table 2.5, where we use sales as the explained variable. We find a minuscule but statistically significant coefficient on the outage hours variable, -0.002, in the full sample of all firms across the four countries we study. This suggests a negative, if economically insignificant relationship, between outage hours and firm performance. In the individual country samples, we find no evidence of a negative association between outages and firm performance. However, the coefficients on both measures of reliability are markedly more negative in this specification. But the coefficient on outages dummy for Tunisia, which is rather large and statistically significant in our earlier specification with sales as explained variable, is smaller and insignificant in the specification using total factor productivity as explained variable. We further examine the robustness of these results using valueadded as the explained variable. The results from this specification, documented in Table 2.8 of Appendix A, show no significant negative association between outages and firm performance for both the full sample of all firms and the country sub-samples, except for Indonesia with a statistically significant coefficient of -0.005 on the outage hours variable.

Finally, across the generator ownership and size categories we find evidence of a negative relationship between outage hours and firm performance for firms that do not own a generator. This result, shown in Table 2.9 of Appendix A, again differs from that in our main specification where the coefficients on both measures of reliability are statistically indistinguishable from zero regardless of the generator ownership status of the firm. Across size classification, we also see evidence of a negative relationship between outage hours and firm performance for both small and large firms. Again, while the results from our main specification in this category are not statistically significant, they are of similar magnitude with the specification using TFP as outcome variable.

2.7 Conclusion

We use a nationally representative cross-sectional survey from the WBES, covering a total of $8,348$ firms across four countries to investigate the relationship between outages and firm performance. In the development literature, there is already a thoroughgoing analysis on firm performance and outages in low-electrification, developing countries. However, a potential concern is that even universally-electrified countries have reliability problems. Yet very little is known about the impacts of outages on firm performance in these countries. Understanding this impact is important as many developing, low-electrification countries now pursue the goal of universal electrification.

We find only weak evidence of a negative association between outages and firm performance across all firms in our sample. This finding holds across sub-samples with and without onsite generators as well as different firm size categories. This result suggests that universal electrification may have been effective towards meeting its policy goals, even in the presence of imperfect reliability. While we find some negative association between outages and firm performance for firms in Tunisia, using sales as the explained variable, the finding is not robust to other specifications using total factor productivity and valueadded as the explained variable. Therefore, given this mixed results and the likely biases in our estimates, we assert that outages in the countries we study do not necessary result in economically significant productivity losses.

Reliable supply of electricity is widely acknowledged as an important input for satisfactory firm performance and economic growth. Yet it is possible for firms, especially the ones in the country we study to adapt to challenges posed by outages — which are relatively infrequent in these countries — such that their productivity is not significantly impacted. It is important to stress this finding as many development institutions and agencies frame universal access to electricity as the pinnacle of electrification goals for developing countries. While universal electrification on its own does not necessarily imply reliable power supply, countries that have attained universal electrification have expended huge capital in reaching the so-called last mile. Usually, these countries have invested in power infrastructure and reliability in urban areas, hence they tend to have a fairly reliable power system relative to countries that have yet to achieve universal electrification. Still, the optimal allocation of electricity sector investment is more nuanced and depends not only on electrification rates and average reliability but also on country-specific conditions. Defining and understanding the country-specific conditions that drive these differences in reliability impacts requires further study.

The results from the overall sample across all four countries in this study intimate that power outages may not be a problem for the average firm operating under conditions of universal electrification, as we find no consistently negative and significant association between outages and firm performance. However, examining country-specific cases indicates that the overall result may conceal some differences across countries and firms. We conclude that while countries with universal electrification may well have reliable supply of power to industry or their firms may be readily able to adapt to outages without disruptions to business operations, firms in other universally-electrified countries may still grapple with reliability. Whether this unreliability can effectively impact firm performance still requires further study. Taking the full sample of firms into consideration, we submit that in countries that have attained universal electrification, there is insufficient evidence of a negative association between outages and productivity. In the case of Tunisia, our results are mixed; the difference we see in total sales between firms experiencing outages and those that do not could be driven by economic outlook faced by affected firms. This finding has implications for the United Nations goal of universal electrification for all countries by 2030. A binary metric has long been used to assess electrification rates in developing countries. But several newer metrics that emphasize reliability have been proposed with the realization that access rates measures fail to embody the extent of reliability. While access rates are a poor measure of reliability, our findings suggest that countries that have achieved universal electrification tend to have a fairly reliable power systems. Admittedly, having a 100% rate of electrification does not translate to a fail-safe power system, but the path to universal electrification, particularly for countries that have attained it through home-grown efforts, entails massive outlay of investments in which power infrastructure in business centers and cities are prioritized.

Finally, our results suggest policymakers should encourage the development of new measures that consider the vulnerability or adaptation capability of a population to limited access and poor reliability. Our findings also show cause for optimism; the weak evidence of a negative association between outages and firm performance that we find in the overall sample suggests that it is possible for firms in countries with universal electrification to successfully adapt to any remaining reliability problems such that performance is not hindered by power outages. Our findings in particular underscore the need for future research to unpack any remaining cross-country heterogeneity in the effects of reliability. With limited data, our study is not able to clearly delineate the factors that make firms in some regions more susceptible to the effects of power outages than firms in other regions. Doing so, however, is the next logical step for helping policymakers to understand when and where reliability investments are most needed.

2.8 Appendix

We provide here additional regression tables detailing other results of interest

Table 2.8 Power Outage Effects on Valueadded by Country

	All	Morocco	Tunisia	Egypt	Indonesia
	(1)	(2)	(3)	(4)	(5)
			Panel A		
Outage Hours	−0.002	−0.003	0.002	−0.000	−0.005*
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)
Observation	4,848	510	550	2,862	926
R-squared	0.525	0.417	0.563	0.506	0.562
			Panel B		
Outages Dummy (0/1)	0.013	−0.196	−0.007	0.067	−0.015
	(0.054)	(0.166)	(0.198)	(0.053)	(0.195)
Observation	4,848	510	550	2,862	926
R-squared	0.525	0.418	0.563	0.506	0.560
Firm-Level Controls	Y	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y

Notes: This table shows OLS estimates for the impact of power outages on firm performance in each of the full sample of firms in all countries (column 1) and each of the four countries (columns 2 through 5). Robust standard errors are clustered at the different regional levels in each country. The measure of outages in Panel A is Outages hours, while in Panel B, outages are measured using the Outages Dummy. Both firm-and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

Table 2.9 Effect of Power Outage on TFP, by Generator Ownership Status and Firm Size

	Generator Ownership		Firm Size		
	Generator	No Generator	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)
			Panel A		
Outage Hours	-0.000	-0.003^{**}	-0.001^{***}	-0.001	-0.002^{**}
	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)
Observation	759	4060	1,926	1,424	1,256
R-squared	0.222	0.035	0.141	0.036	0.125
			Panel B		
Outages Dummy (0/1)	0.033	-0.061	-0.060	-0.034	-0.057
	(0.222)	(0.034)	(0.037)	(0.080)	(0.114)
Observation	759	4060	1,926	1,424	1,256
R-squared	0.587	0.447	0.141	0.036	0.124
Firm-Level Controls	Y	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y

Notes: This table shows OLS estimates for the impact of power outages on firm performance across generator ownership (columns 1 and 2) and firm size categories (columns 3 through 5), for firms in all four countries. Robust standard errors are clustered at the 39 different regional levels in the full sample. The measure of outages in Panel A is Outages Hours, while in Panel B, outages are measured using the Outages Dummy. Both firm-and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, access to finance foreign ownership, government ownership and city size.

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

Table 2.10 First Stage OLS

	Outages	
	(Outage Hours)	(Outages Dummy (0/1)
Mean Outage Hours	0.676^{***}	
	(0.092)	
Mean Outages Dummy (0/1)		0.940^{***}
		(0.035)
Manager's Experience	0.041^{***}	-0.000
	(0.014)	(0.000)
No. Permanent Workers	-0.000	-0.000^{*}
	(0.001)	(0.000)
Generator	2.976^{***}	0.885^{***}
	(0.490)	(0.016)
Small Firm	0.433	-2.135^{***}
	(0.459)	(0.077)
Medium Firm	0.428	-1.227^{***}
	(0.483)	(0.813)
Age of Firm	0.001	-0.000
	(0.001)	(0.000)
Foreign Ownership	0.922	0.792
	(0.585)	(0.101)
Government Ownership	-0.021	-0.046
	(1.144)	(0.190)
Bigger City	-0.181^{**}	-0.176
	(0.553)	(0.093)
Big City	-1.123^{***}	-0.819^{***}
	(0.453)	(0.079)
Medium City	-0.456	-0.344^{***}
	(0.526)	(0.087)
Finance Obstacle	-0.456	0.085^{**}
	(0.526)	(0.045)
Observation	8,031	8,031
Montiel-Pflueger F-Stat	53.26	674
R^2	0.014	0.110

Notes: Robust standard errors in parenthesis. In columns 1 and 2, standard errors are clustered at the 39 different regional levels. F-Stat is the IV First Stage F-test of instrument strength. Outage Hours is the total duration of outages a firm experienced in a month. Outages Dummy (0/1) is defined as 1 if a firm experienced an outage in the past year, and 0 otherwise. The instruments are: Mean Outage Hours and Mean Outages Dummy. Small City is omitted in the city-size category, while Large Firm is omitted in the firm-size category.

$p<0.1$; $p<0.05$; $^{**}p<0.01$

Table 2.11 Power Outage Effects on Logged Sales by Country — IV Estimates

	Morocco	Tunisia	Egypt	Indonesia
	(1)	(2)	(3)	(4)
		Panel A		
Outage Hours	−0.001	0.002	0.004***	−0.003*
	(0.003)	(0.001)	(0.001)	(0.002)
Montiel-Pflueger F-Stat	46.87	17.79	6.173	33.38
Observation	1,246	1,081	4,522	1,194
R-squared	0.394	0.547	0.448	0.550
		Panel B		
Outages Dummy (0/1)	−0.094	−0.099**	0.068	0.058
	(0.157)	(0.040)	(0.089)	(0.184)
Montiel-Pflueger F-Stat	54.96	19.98	6.14	75.09
Observation	1,246	1,081	4,522	1,182
R-squared	0.400	0.548	0.448	0.550
Firm-Level Controls	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y

Notes: This table shows instrumental variable estimates for the impact of power outages on firm performance in each of the four countries (columns 1 through 4). Robust standard errors are clustered at the different regional levels in each country. The measure of outages in Panel A is Outage Hours, while in Panel B, outages are measured using the Outages Dummy. Both firm-and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, access to finance, foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

Table 2.12 Power Outage Effects on Logged Sales by Generator Ownership Category in Each Country — IV Estimates

	Morocco Generator (1)	Tunisia Generator (2)	Egypt Generator (3)	Indonesia Generator (4)
		Panel A		
Ouatges Dummy (0/1)	0.135	−0.266	−0.257	−0.037
	(0.423)	(0.345)	(0.166)	(0.250)
Montiel-Pflueger F-Stat	26.05	14.05	25.08	91.37
Observation	126	110	561	292
R-squared	0.694	0.738	0.621	0.521
	No Generator	No Generator	No Generator	No Generator
		Panel B		
Outages Dummy (0/1)	0.145	-0.113^{**}	0.091	0.009
	(0.180)	(0.054)	(0.121)	(0.165)
Montiel-Pflueger F-Stat	59.35	19.40	5.479	71.95
Observation	1,120	971	3,961	890
R-squared	0.372	0.538	0.405	0.528
Firm-Level Controls	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y

Notes: This table shows instrumental variable estimates for the impact of power outages on firm performance in each of the four countries across generator ownership (columns 1 through 4). Robust standard errors are clustered at the different regional levels in each country. Panel A shows the impact of power outages on firm performance for firms owning a generator, using the Outages Dummy measure. Panel B shows the impact of power outages on firm performance for firms without a generator, using the Outages Dummy measure. Both firm- and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, access to finance, foreign ownership, government ownership and city size.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

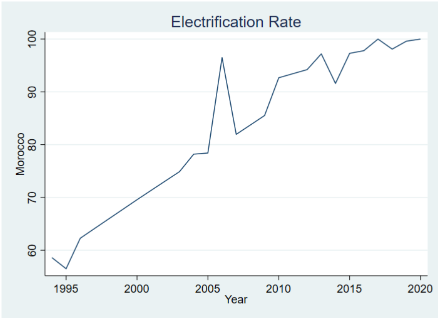

Figure 2.9 This figure shows the electrification rate for Morocco, which grew rapidly in the 90s and 2000s, but only reached 100% in 2020.

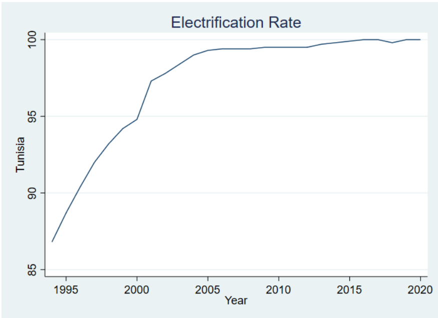

Figure 2.10 This figure shows the electrification rate for Tunisia. While electrification rate has peaked since the mid 2000s, it reached 100% in 2016.

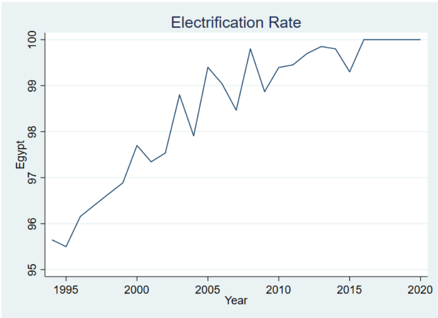

Figure 2.11 This figure the electrification rate for Egypt, which has been as high as 95% since 1994, but only reached a 100% in 2016

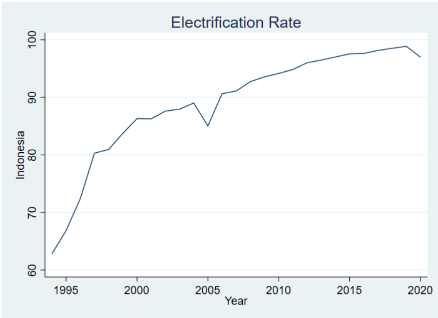

Figure 2.12 This figure shows the electrification rate of Indonesia, which grew rapidly in the 90s, and reached a peak of 99%

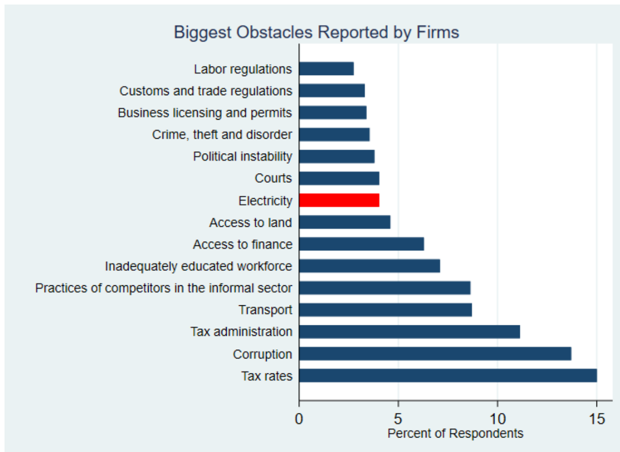

Figure 2.13 This figure shows the self-ranking of the biggest obstacles faced by firms in Morocco. Tax rates is ranked as the biggest obstacle while electricity, marked in red, is ranked 9^{th} amid the 15 obstacles identified from firms responses.

Figure 2.14 This figure shows the self-ranking of the biggest obstacles faced by firms in Tunisia. Political instability is ranked as the biggest obstacle while electricity, marked in red, is ranked 12^{th} amid the 15 obstacles identified from firms responses.

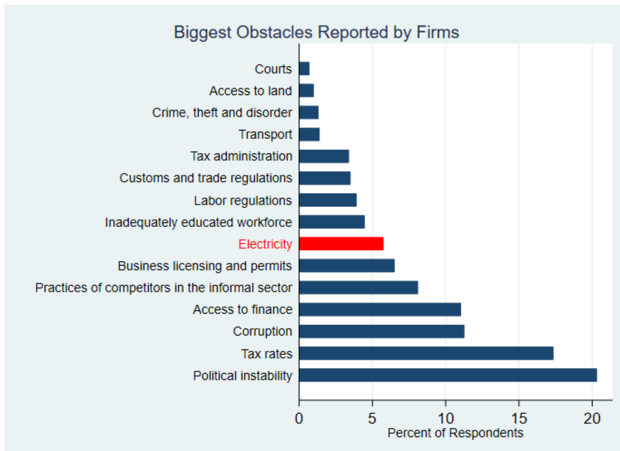

Figure 2.15 This figure shows the self-ranking of the biggest obstacles faced by firms in Egypt. Political instability is ranked as the biggest obstacle while electricity, marked in red, is ranked 7^{th} amid the 15 obstacles identified from firms responses.

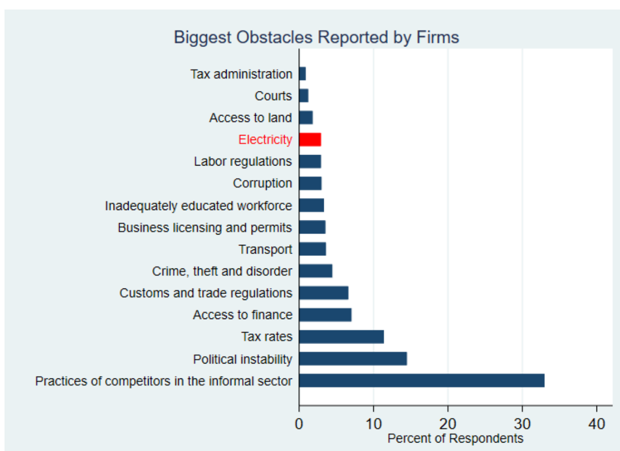

Figure 2.16 This figure shows the self-ranking of the biggest obstacles faced by firms in Indonesia. Practices of competitors is ranked as the biggest obstacle while electricity, marked in red, is ranked 12^{th} amid the 15 obstacles identified from firms responses.

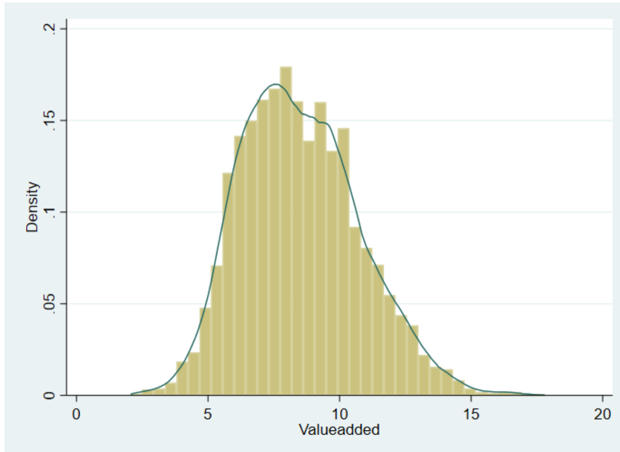

Figure 2.17 This figure shows the distribution of valueadded among all firms across the countries we study, which, overall follows a normal distribution.

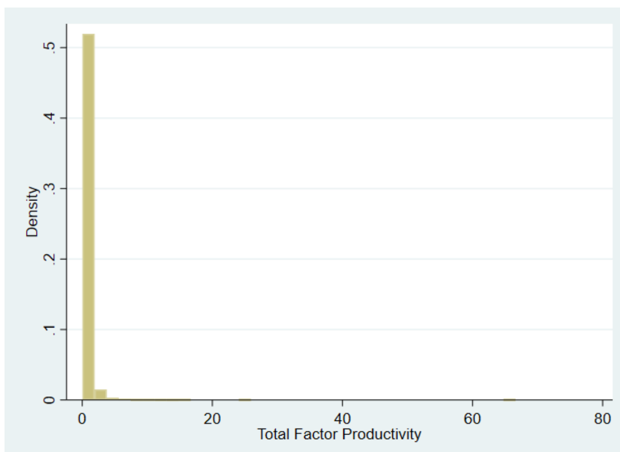

Figure 2.18 This figure shows the distribution of total factor productivity among all firms across the countries we study. The distribution appears to be skewed to the left, but for most firm the TFP values fall between 0 and 2, with some outliers above 20 .

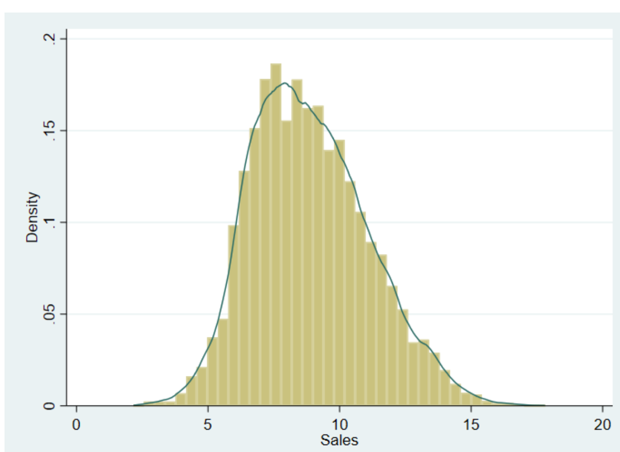

Figure 2.19 This figure shows the distribution of sales among all firms across the countries we study, which also follows a normal distribution.

CHAPTER 3

ESTIMATING THE VALUE OF CONCENTRATING SOLAR POWER WITH ANCILLARY SERVICES

This paper has been submitted to Applied Energy.

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Abstract

Ancillary services, such as spinning reserves, can provide grid reliability and contribute to profitability of an energy resource. We exercise an existing dispatch optimization model to estimate the profitability of a concentrating solar power plant by incorporating the sale of spinning reserves in the ancillary service market using the National Renewable Energy Laboratory's System Advisor Model to simulate the operation of a concentrating solar power plant within a 72-hour rolling horizon framework. Assuming a price-taker approach with day-ahead energy and spinning reserve prices from both the California Independent System Operator and Electricity Reliability Council of Texas, we find that selling spinning reserves in addition to electric energy increases plant profitability by up to 7% with perfect knowledge of day-ahead pricing and solar resource availability. This finding suggests that spinning reserve markets offer significant value streams to concentrating solar power plants that can leverage thermal energy storage to offer reliable production in the short-to-medium term.

3.1 Introduction

Concentrating solar power (CSP) tower technologies utilize a field of sun-tracking heliostats to capture direct normal irradiance (DNI). If not used immediately to generate electricity, this energy is then transported to a thermal storage for later use. According to International Energy Agency data, generation from concentrating solar power increased from 0.9 TWh in 2009 to 14.5 TWh in 2020 [IEA, 2021]. CSP was initially on a commercial scale in early 2000s with most of the growth in CSP capacity taking place in the past five years relative to the time of this writing, due to a significant reduction in cost and increased policy support attributed to plants with operations in China, Morocco, and South Africa [Mehos et al., 2015]. Du et al. [2018] discuss the economic justification for concentrating solar power, particularly in geographic areas with high solar penetration.

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This paper focuses on the power tower, which is the second-most deployed CSP technology globally after the parabolic trough [Islam et al., 2018]. The power tower configuration can achieve high concentration ratios and correspondingly high temperatures relative to other CSP technologies and can be sized for utility-scale generation. Further, the operational cost associated with this technology is not as high as those of other CSP technologies [Hamilton et al., 2020]. Wagner et al. [2018] detail advantages of the power tower over other CSP technologies and fossil-fueled alternatives. CSP is particularly attractive because of the flexibility it affords to a regional grid when paired with thermal energy storage. However, CSP adoption rates in the Organisation for Economic Co-operation and Development — a coalition of relatively wealthy and democratic countries — remain low. Gonzalo et al. [2019] review performance of this relatively new technology in an effort to better understand opportunities for improvements. Yet, for states within the Southwest U.S. with high DNI, CSP offers a viable option for power generation. More globally, the countries in which CSP has been deployed on a commercial scale also typically have high DNI, which is a requisite for low-cost power generation. In China, CSP projects are projected to drive the 2050 target of increasing the share of renewables to 27.5 percent of all energy generation [Wang et al., 2017]. Morocco has set an ambitious plan of developing 2 GW of solar power by 2020 through public-private partnership. Both Spain and South Africa started supporting renewable energy through a feed-in-tariff program, which guarantees an above-market price for producers [Couture et al., 2010]. By 2012, Spain had installed CSP generation capacity totaling 1.8 GW. Other countries with growing CSP capacity have instituted various support mechanisms to foster the generation of electricity from CSP systems such as a fixed-price policy, which guarantees stability through offering a minimum price, and feed-in-tariff.

As the cost of CSP continues to fall, we predict an increase in investment in CSP. In this scenario, the participation of CSP in electricity markets is likely to rise, while setting in motion the potential for engagement in ancillary service markets. Ancillary services are functionalities provided by plant owners and generators, in addition to energy sales, that help maintain the reliability of the grid and include spinning and non-spinning reserves, regulation service and black-start service, among others. In addition to bolstering grid reliability, ancillary services can contribute to the profitability of a plant [Cardoso et al., 2017]. In evaluating ancillary service markets, there are two important considerations: (i) the size of the market which determines whether the prospect of entrance is appealing, and (ii) the clearing price which indicates the extent to which an entrant into the market may be profitable [MacDonald et al., 2022]. Participation of CSP in ancillary service markets — a market in which spinning reserves are traded — is also growing. In Chile, for example, CSP plants can participate in both energy and ancillary service markets [McPherson et al., 2020]. However, due to high installed generation capacity in the country, the price of ancillary services tends to be low.

The economics of falling CSP costs should imply that it will become more attractive and profitable as an investment, while also playing a key role in the drive towards decarbonization and, ultimately, net-zero emissions. Moreover, as the penetration of renewable energy increases, the need for ancillary services is expected to grow correspondingly. However, the International Energy Agency estimates that an average annual growth rate of 31% in CSP power generation is required between 2020 and 2030 to reach net-zero emissions IEA [2021]. Achieving this growth will require more policy support. Studies on CSP compare different scenarios with and without storage, and include the provision of both energy and ancillary services; studies show that thermal energy storage can increase the value of CSP and that adding ancillary services can significantly increase the value of CSP in several Western states in the United States [Sioshansi and Denholm, 2010]. Specifically, Madaeni et al. [2011] find that the provision of ancillary services, in addition to the sale of energy, can increase the value of a CSP plant by 17%. While they consider other ancillary services such as capacity, we focus only on spinning reserves. It is important to re-examine both the value and profitability of CSP under different locations and markets, using updated cost information and the latest dynamics of the System Advisor Model [Blair, 2014], a techno-economic model designed to estimate the cost of renewable energy.

In order to position CSP as a preferred technology among renewable energy sources, given the many benefits that it can provide to the grid, it is important to evaluate its value according to current trends in costs, technological innovation and market structure. Our contribution, therefore, is to provide an assessment of the impact of ancillary services on the profitability of a CSP plant, offering spinning reserves in addition to energy services in the power market. The demand response time of 10 minutes is sufficient for a CSP plant to ramp up to generate spinning reserves. Moreover, the demand for spinning reserves is usually higher than that for non-spinning reserves. We use DNI data to simulate the exact temperature in both Southern California and Western Texas and maximize the value of a CSP plant, assuming that such a plant is a *price taker*, i.e., that the market-clearing price is taken as given. By contrast, a model with multiple plants with an objective of aggregate cost minimization is known as a *production cost model*. We explain these approaches in Section 3.2 of this paper.

While several papers have estimated the value of CSP using a price-taker approach, our main objective is to model, in particular, the sales of spinning reserves — a type of ancillary services — and assess how this can impact the profitability of a CSP plant. Independent system operators' need for ancillary services from dispatchable resources such as CSP has been recognized [Forrester, 2014, Mena et al., 2019]. This supply of ancillary services is pivotal to ensuring that demand for electricity is met, particularly during contingencies that are often difficult to predict. We contribute to this subject by exploring the additional value that ancillary services can provide to the grid and to the CSP plant owner. To this end, we leverage several works in the CSP literature, including Sioshansi and Denholm [2010] and Madaeni et al. [2011]. However, we employ a mixed-integer linear program that captures the nuances of the costs and penalties associated with operating a CSP plant, while taking into consideration large thermal energy storage capacity.

The remainder of the paper is organized as follows: Section 3.2 provides a literature review of the value of CSP, different techniques used in estimating this value, and the provision of ancillary services. Section 3.3 discusses the modified formulation of the dispatch optimization model relevant to the sale of spinning reserves. Section 3.4 describes the case studies across multiple time horizons and markets. Section 3.5 shows the results of the different case studies. Section 3.6 concludes with a summary and implication of our results for investments in CSP and policy making, and future work on potential income streams.

3.2 Literature Review

Ancillary services are vital to the reliability of a regional grid. Rebours et al. [2007] stress their importance in ensuring system stability. However, the authors also highlight a number of fundamental challenges associated with the provision of these services, including the correct valuation and the uncertainty of revenues for resources providing these services. Carlson et al. [2012] show that the development and implementation of energy and ancillary service markets result in total savings between $2.1 billion and $3.0 billion between 2007 through 2010. Ela et al. [2013] argue, with supporting studies, that frequency response — a type of ancillary service that offers power to the grid within a few seconds to 10 minutes — has been on the decline in the United States. They cite physical and institutional reasons for this attrition, but emphasize the lack of proper incentives to encourage participation and propose a market design that incentivizes the provision of frequency response. In fact, several other studies emphasize the need to remove barriers that prevent the participation of variable renewable sources of energy generation in ancillary service markets [Holttinen et al., 2016, Fernandes et al., 2016]. Banshwar et al. [2017], in a review of energy and ancillary service markets around the world, maintain that there is still a need for modification of energy markets to better integrate the provision of ancillary services from renewable sources of generation.

Evidence from power markets show, however, that there is a growing participation of renewable energy sources in ancillary service markets. This growth is propelled, in part, by innovations that enhance the dispatchability of renewable energy sources. Mashhour and Moghaddas-Tafreshi [2010] propose the integration of distributed generation into a virtual power plant, which, in turn, facilitates the aggregation of distributed energy resources to provide either electrical energy or system-support services. A virtual power plant combines, in a complementary manner, different sources of renewable and non-renewable energy sources in such a way that fluctuation in variable generation is counteracted by generation sources with storage. Several other studies propose combining CSP with other sources of renewable energy. For example, Fang and Zhao [2020] study a joint system that encompasses both wind farms and CSP plants. The design of this system is such that CSP plants use thermal energy storage to contribute additional power, which can be used to compensate for fluctuations in wind power generation, while also providing ancillary services. Using case studies of different bidding models, they conclude that a joint system offers improved value compared to individual plants. Similarly, Tan and Zhang [2017] propose supporting wind power plants with a battery energy storage system. While it has been shown that wind turbines can furnish certain frequency response services, other ancillary services such as spinning reserves may also be provided by coupling battery energy storage systems with renewable generation resources. Miller and Clark [2010] examine advances in wind plant controllers, and how these can position plants to provide ancillary services such as frequency response through coordination of real and reactive power of multiple wind turbines, making the plant function as a single grid when other conventional generation sources are unavailable. In spite of the demonstrated potential of wind power plants to provide ancillary services, Miller and Clark [2010] argue that there are concerns about potential challenges. For example, Hansen et al. [2016] use case studies to highlight the need for coordination in wind power plants to avoid unstable power system operation when multiple plants are called upon to provide ancillary services. Attya et al. [2018] also examine technical and other challenges of wind turbines associated with the maintenance of power system stability.

The functionalities such as ancillary services to energy provision in CSP dispatch has been hypothesized to increase its economic value. Earlier studies estimate the value delivered [Sioshansi and Denholm, 2010, Madaeni et al., 2011, Narimani et al., 2017]. While they focus on other variable renewable energy sources, and not CSP, Kahrl et al. [2021] find that the participation of standalone variable renewable energy sources (i.e., without energy or storage) in the ancillary service market provides little incremental value. However, for hybrid sources of energy generation, i.e., renewable energy sources paired with battery storage, incremental revenues are significant. The profitability of a CSP plant could also be impacted by market configuration and rules. In a study of countries including Australia, Chile, China, Dubai, Morocco, Spain, South Africa and the United States, McPherson et al. [2020] show that jurisdiction-specific policies hamper appropriate renumeration — which could be a capacity payment — of CSP, given its flexibility and dispatchability.

In assessing the economic value of electricity sources, the levelized cost of energy has been widely used for calculating the value of renewable energy sources, including CSP. However, the flaws of this method are well documented in Dowling et al. [2017a], Kost et al. [2013] and Lizarraga-Garcia et al. [2013]. Dowling et al. [2017b], in a review of methods assessing the economic value of CSP, show that studies that use a levelized cost of energy approach tend to undervalue the revenue-generating potential of CSP. Given that CSP plants with storage can participate in the provision of ancillary services and ultimately contribute to grid reliability, they advocate for more nuanced techno-economic assessments. CSP plants, while different from conventional sources of renewable energy generation, are unique for their dispatchability. For example, Dinter and Gonzalez [2014] study the Andasol power station, which is a 150-megawatt concentrated power station located in Andalusia, Spain. They found that the station was able to produce energy continuously for a period of one week in September, 2012. Using actual data from Andasol, the authors demonstrate that the plant is able to efficiently shift energy and provide a range of ancillary services. This dispatchability makes CSP as reliable as other conventional sources of energy generation, such as fossil fuel and natural gas plants. The capability of a CSP plant to operate continuously provided there is sufficient DNI has been replicated in several other experiments. Denholm et al. [2015] posit that CSP with thermal energy storage provides multiple value streams stemming from the sale of energy and ancillary services. Taking advantage of these value streams, CSP can become more attractive.

Different optimization models have been used to address the question of CSP dispatch. Pousinho et al. [2014] use a mixed-integer linear program to solve the problem of short-term self scheduling and coordination of a wind power plant and CSP. There is an abundance of studies that use various optimization techniques, including mixed-integer linear programming [Yang et al., 2018, Wagner et al., 2017]. Yu et al. [2019] also employ a mixed-integer linear program within a scenario-based stochastic framework to determine optimal offering strategies. In our paper, we extend Wagner et al. [2017] to include ramping limits and the opportunity to sell spinning reserves while assuming a price-taker approach. Our model also captures the nuances of the costs and penalties associated with operating a CSP plant.

Martinek et al. [2018] show that two approaches are valid for evaluating the performance and value of CSP systems, namely, a price-taker approach and a production cost model. We argue that the price-taker approach is more appropriate in that it has been adopted to calculate the value of CSP and other renewable sources of energy generation, using different optimization modeling techniques. A price taker has negligible influence on the market-clearing price of electricity; hence, it seeks to maximize profits by making an optimal bid in the market [Honkapohja, 1980, Mathur et al., 2017]. Martinek et al. [2018] provide the first comparative study of the differences between the computationally simpler price-taker approach and the complex production-cost model, and find that the results are similar. As a result of the tractability of the price-taker approach, many studies have utilized it to estimate the value and bidding behavior of different sources of energy generation. For example, Yucekaya [2013] examine bidding strategies of a price-taker coal plant in the Turkish power market. They highlight that bids below the clearing market price are accepted and rewarded with the market-clearing price. They therefore propose a marginal cost-based Monte Carlo method for making winning bidding strategies. Similarly, Nojavan et al. [2015] use information gap decision theory to inform an optimal bidding strategy for a price-taker generation station. They show that the risk appetite of a price-taker generator in the face of market price uncertainty can affect profitability. Ilak et al. [2014] use a price-taker approach to analyze the participation of a hydropower plant in the day-ahead market for the provision of both energy and ancillary services. To determine energy prices, they construct marginal cost curves for energy and ancillary services, which they then integrate into a mixed-integer linear program to determine expected daily profits for a variety of scenarios based on stochastic prices. Bai and Zhai [2017] adopt a price-taker approach to solve the self-scheduling problem of a hydroelectric power plant. Based on results from their optimization model, they conclude that price-taker hydro plants can effectively self-schedule electricity generation and make optimal bidding decisions. Rahimiyan and Baringo [2015] consider a virtual plant in a price-taker approach that agglomerates different sources of energy generation in a two-stage game setting, where bidding in the day-ahead market is decided in the first stage, and, in the second stage, bidding in the real-time market. They argue that this strategy can be applied by power generation plants participating in energy markets. Studying a combined cycle plant operating at part load, Variny and Mierka [2009] demonstrate that depending on the extent and type of ancillary services provided, fuel savings can be achieved. Finally, Campos and Reneses [2014] use a price-based unit commitment model to co-optimize generation and reserve operations of a combined cycle gas plant. This body of work lends credence to the price-taker approach, and provides a frame of reference for the estimation of the value a CSP plant, using plant simulation in the System Advisor Model, while modeling our setting as a mixed-integer linear program.

3.3 Modified Dispatch Optimization Model with Ancillary Services

The optimization model in our work is based upon the linear portion of Cox et al. [2022] and incorporates thermal energy storage at half-hourly fidelity over a rolling time horizon. The model maximizes plant revenue from the sale of electricity less the costs of operations and maintenance and purchases from the grid due to dispatch decisions made throughout the time horizon. We extend the dispatch model to include the sale of spinning reserves, and define the modified model as $(\mathcal{S}')$.

3.3.1 Notation

Here, we introduce notation used for the model extension. In general, upper-case letters denote parameters while lower-case letters are reserved for variables. We use lower-case letters for indices and upper-case script letters for sets.

Table 3.1 Real-time dispatch model, $(\mathcal{S}')$, notation.

Indices and Sets	
$t \in \mathcal{T}$	Time periods

Parameters		**Units**
α	Conversion factor between unitless and monetary values	\$
η^{D}	Cycle nominal efficiency	$\mathrm{kW_e/kW_t}$
Δ^d	Minimum duration for continuous spinning reserves	h
Δ^r	Spinning reserve demand response time	h
Δ_t	Duration of period t	h
C^{c}	Operating cost of power cycle	$\$/\mathrm{kWh_e}$
C^{chsp}	Penalty for power cycle hot start-up per start	\$
C^{csb}	Operating cost of power cycle standby operation	\$/h
C^{csu}	Penalty for power cycle cold start-up per start	\$
$C^{\delta\mathrm{W}}$	Penalty for change in power cycle production	$\$/\mathrm{kW_e}$
C^{r}	Operating cost of heliostat field and receiver	$\$/\mathrm{kWh_t}$
C^{rhsp}	Penalty for receiver hot start-up per start	\$
C^{rsu}	Penalty for receiver cold start-up per start	\$
C^{vW}	Penalty for change in power cycle production beyond designed limits	$\$/\mathrm{kW_e}$
D_t	Time-weighted discount factor in period t	-
F_t^{sr}	Spinning reserves sale price in period t	$\$/\mathrm{kWh_e}$
M	A sufficiently large number	-
$\hat{P}$	Average electricity sale price	$\$/\mathrm{kWh_e}$
P_t	Electricity sale price in period t	$\$/\mathrm{kWh_e}$
$\dot{W}^{\delta+}$	Power cycle ramp-up designed limit	$\mathrm{kW_e}$/h
$\dot{W}^{\mathrm{u}}$	Power cycle electric power rated capacity	$\mathrm{kW_e}$
$W_t^{\mathrm{u}+}$	Maximum power production when starting generation in period t	$\mathrm{kW_e}$/h
$\dot{W}^{\mathrm{v}+}$	Power cycle ramp-up violation limit	$\mathrm{kW_e}$/h

Static Decision Variable		**Units**
$\hat{s}$	Discounted thermal energy in storage at the end of the problem horizon	$\mathrm{kWh_t}$

Time-indexed Continuous Decision Variables		**Units**
r_t^{s}	Spinning reserves power sold to the grid in period t	$\mathrm{kW_e}$
s_t	Usable thermal energy in period t	$\mathrm{kWh_t}$
$\dot{w}_t$	Power cycle electricity generation in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\delta+}$	Power cycle ramp-up in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\delta-}$	Power cycle ramp-down in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\mathrm{p}}$	Electrical power purchased from the grid in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\mathrm{s}}$	Electrical power sold to the grid in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\mathrm{v}+}$	Power cycle ramp-up beyond designed limit in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\mathrm{v}-}$	Power cycle ramp-down beyond designed limit in period t	$\mathrm{kW_e}$
x_t^{r}	Thermal power delivered by the receiver in period t	$\mathrm{kW_t}$

Time-indexed Binary Decision Variables	
y_t	1 if cycle is generating electric power in period t; 0 otherwise
y_t^{chsp}	1 if cycle hot start-up penalty is incurred in period t

Table 3.1 Continued

	(from standby); 0 otherwise
y_t^{csb}	1 if cycle is in standby mode in period t; 0 otherwise
y_t^{csdp}	1 if cycle is shutting down in period t; 0 otherwise
y_t^{csup}	1 if cycle cold start-up penalty is incurred in period t (from off); 0 otherwise
y_t^{cgb}	1 if cycle begins electric power generation in period t; 0 otherwise
y_t^{rhsp}	1 if receiver hot start-up penalty is incurred in period t (from standby); 0 otherwise
y_t^{rsb}	1 if receiver is in standby mode in period t; 0 otherwise
y_t^{rsdp}	1 if receiver completes shut down in period t; 0 otherwise
y_t^{rsup}	1 if receiver cold start-up penalty is incurred in period t (from off); 0 otherwise
z_t	1 if spinning reserves are allocated for contingency use in time period t; 0 otherwise

3.3.2 Objective Function

We modify the objective function given in Cox et al. [2022], which maximizes the profit from sale and purchases of electrical energy less the costs for running the plant to determine total net revenue. The modified objective function includes a second term shown in red that represents the non-discounted profit from spinning reserves.

$$(\mathcal{S}') \quad \text{maximize} \quad \sum_{t\in\mathcal{T}} \Bigg[D_t \Delta_t P_t \left(\dot{w}_t^{\mathrm{s}} - \dot{w}_t^{\mathrm{p}}\right) + \Delta_t F_t^{sr} r_t^{s}$$
$$- \Bigg[\left(C^{\mathrm{csu}} y_t^{\mathrm{csup}} + C^{\mathrm{chsp}} y_t^{\mathrm{chsp}} + \alpha y_t^{\mathrm{csdp}} \right) + \left(C^{\delta\mathrm{W}} (\dot{w}_t^{\delta^+} + \dot{w}_t^{\delta^-}) + C^{\mathrm{vW}} (\dot{w}_t^{\mathrm{v}^+} + \dot{w}_t^{\mathrm{v}^-}) \right)$$
$$+ \left(C^{\mathrm{rsu}} y_t^{\mathrm{rsup}} + C^{\mathrm{rhsp}} y_t^{\mathrm{rhsp}} + \alpha (y_t^{\mathrm{rsb}} + y_t^{\mathrm{rsdp}}) \right) + \Delta_t \left(C^{\mathrm{c}} \dot{w}_t + C^{\mathrm{csb}} y_t^{\mathrm{csb}} + C^{\mathrm{r}} x_t^{\mathrm{r}} \right) \Bigg] \Bigg] + \hat{P} \eta^{\mathrm{D}} \hat{s} \qquad (3.1)$$

3.3.3 Constraints

The constraints applied to the model are taken from Cox et al. [2022], which are found in Appendix A. These include constraints for the receiver, energy balance, power cycle, and grid operations. With the addition of spinning reserves, we account for how it interacts with electricity generation, ramping, sales, and thermal storage. These constraints enforce rules for participating in a spinning reserves market without any energy expenditure tied to their sale; that is, we assume that revenues for the plant are calculated under the premise that the grid never calls upon the plant to increase output. This assumption is consistent with that given in Sioshansi and Denholm [2010]; its validity is justified by the following two arguments: (i) spinning reserves are typically not deployed [Kempton and Tomić, 2005]; and, (ii) our model is deterministic. These constraints are as follows:

Additional Ancillary Services Constraints

$$\dot{w}_t + r^s_t \leq \dot{W}^{\mathrm{u}} \quad \forall t \in \mathcal{T} \tag{3.2a}$$
$$r^s_t \leq \Delta^r(\dot{W}^{\delta+} + \dot{W}^{\mathrm{v}+}) \cdot z_t \quad \forall t \in \mathcal{T} \tag{3.2b}$$
$$z_t \leq y_t \quad \forall t \in \mathcal{T} \tag{3.2c}$$
$$\frac{\Delta^d(\dot{w}_t + r^s_t)}{\eta^D} - M \cdot (1 - z_t) \leq s_t \quad \forall t \in \mathcal{T} \tag{3.2d}$$

Constraint (3.2a) ensures that electricity generation combined with spinning reserves must be less than or equal to the power cycle electric power rated capacity for the plant. Constraint (3.2b) restricts spinning reserves according to the positive ramping limits of the power cycle and the required response time while participating in the spinning reserves market. In constraint (3.2c), we ensure that spinning reserves are sold only if the power cycle is generating electricity. Constraint (3.2d) ensures that if spinning reserves are sold, there must be sufficient thermal storage to meet both the current output and the spinning reserves for the entire contracted duration. Constraints (3.2c) and (3.2d) introduce the use of a binary variable, z_t, which indicates whether the CSP plant is participating in the spinning reserves market or not. To execute this constraint, the following value suffices:

$$M = \frac{\Delta^d(\dot{W}^u)}{\eta^D}$$

We include a power cycle ramping constraint:

$$\frac{\dot{w}^{\delta+}_t - \dot{w}^{\delta-}_t}{\Delta^r} + \frac{r^s_t}{\Delta^{\mathrm{r}}} \leq \tag{3.3}$$
$$\dot{W}^{\delta^+} + \dot{W}^{\mathrm{v}^+} + \left(\frac{\eta^{\mathrm{amb}}_t}{\eta^{\mathrm{D}}} W^{\mathrm{u}^+}_t - \dot{W}^{\delta^+} - \dot{W}^{\mathrm{v}^+}\right) y^{\mathrm{cgb}}_t \quad \forall\, t \in \mathcal{T}$$

Constraint (3.3) is similar to the power cycle ramping constraints in Cox et al. [2022], includes a spinning reserves term, and creates an upper bound on the power cycle ramping variables if power is being generated and spinning reserves are being sold. Power cycle ramping is limited with ramping design, power cycle capacity, ramp-up violation limits, and whether production is started or ended in a current period.

3.4 Market-driven Case Studies

We explore three case studies, to which we refer as: Rice 2010 in California, Rice 2020 in California, and Odessa 2020 in Texas. Figure 3.1 shows the locations of Rice and Odessa. Rice has been identified as a potential location for a CSP plant due to the availability of ample solar resource. Using a dispatch optimization model to evaluate the performance of a CSP Plant, Wagner et al. [2018] find promising results. Similar to Rice, Odessa has abundant solar resource, making it a desirable location for a CSP plant, as we discuss.

Figure 3.1 Locations of Rice, California and Odessa, Texas (Google, 2022)

3.4.1 Representative CSP Plant

We model a notional CSP plant with thermal energy storage. Energy flows through the plant in two procedures. The first is through a collection of heliostats, which redirect sunlight to a receiver that captures heat and transfers it to molten salt that is then stored in a hot storage tank. The second transfers the thermal energy into electric energy. A heat transfer between the molten salt and steam takes place in a power cycle consisting of a system of shell-and-tube heat exchangers, feedwater components, steam turbines, and a steam condenser. The power cycle produces energy sold to the utility or grid. The amount of energy production depends on inputs such as season, weather, and time of day. Collection and production can be concurrent or separate with the presence of thermal energy storage. The notional plant design has a nominal generation capacity of 110 MW from a steam Rankine cycle, and approximately 10 hours of thermal storage. We assume that the plant operating fluid is the commonly-used mixture of sodium nitrate and potassium nitrate, which limits the operating temperature to a maximum of 565 $^\circ C$. The plant design used here is consistent with that given in Cox et al. [2022].

We solve our dispatch optimization model, $(\mathcal{S}')$, on a 72-hour rolling horizon with 30-minute fidelity over a year. The model is rolled forward every 24 hours based on conditions provided by the plant simulation, and in each 72-hour instance, full knowledge of market prices and weather conditions is assumed. Figure 3.2 depicts the planning rolling horizon.

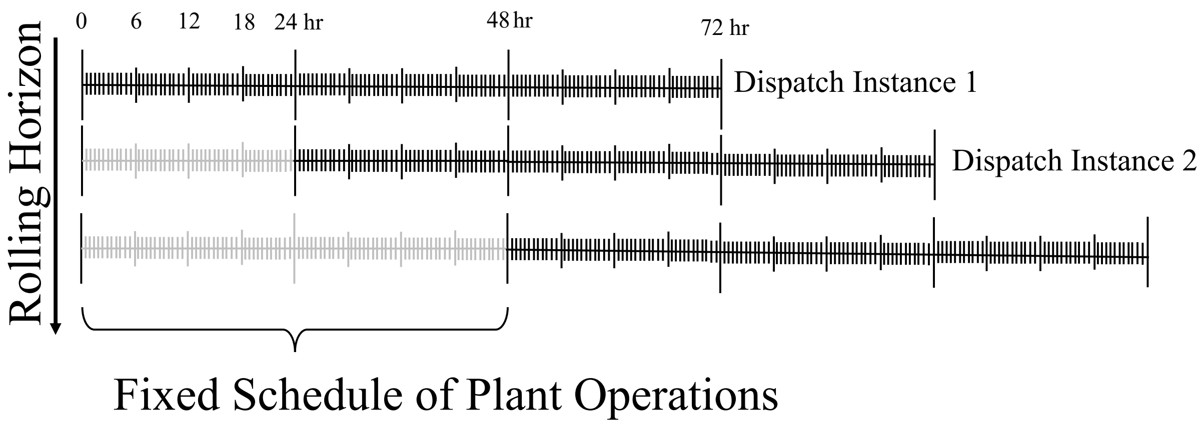

Figure 3.2 Representation of a 72-hour rolling time horizon used in $(\mathcal{S}')$.

3.4.2 Direct Normal Irradiance

We use DNI data from Southern California and Western Texas in the three case studies (Rice 2010, Rice 2020, Odessa 2020). These cases are so named because we derive the DNI data from Rice, California and Odessa, Texas using the National Solar Radiation Database [Sengupta et al., 2018], which holds a serial collection of hourly and half-hourly values of meteorological data. Figure 3.3 shows, in three panels, a heat map summarizing the DNI for the three different cases. It is evident that there is a high measure of DNI all year round, especially in the summer months.

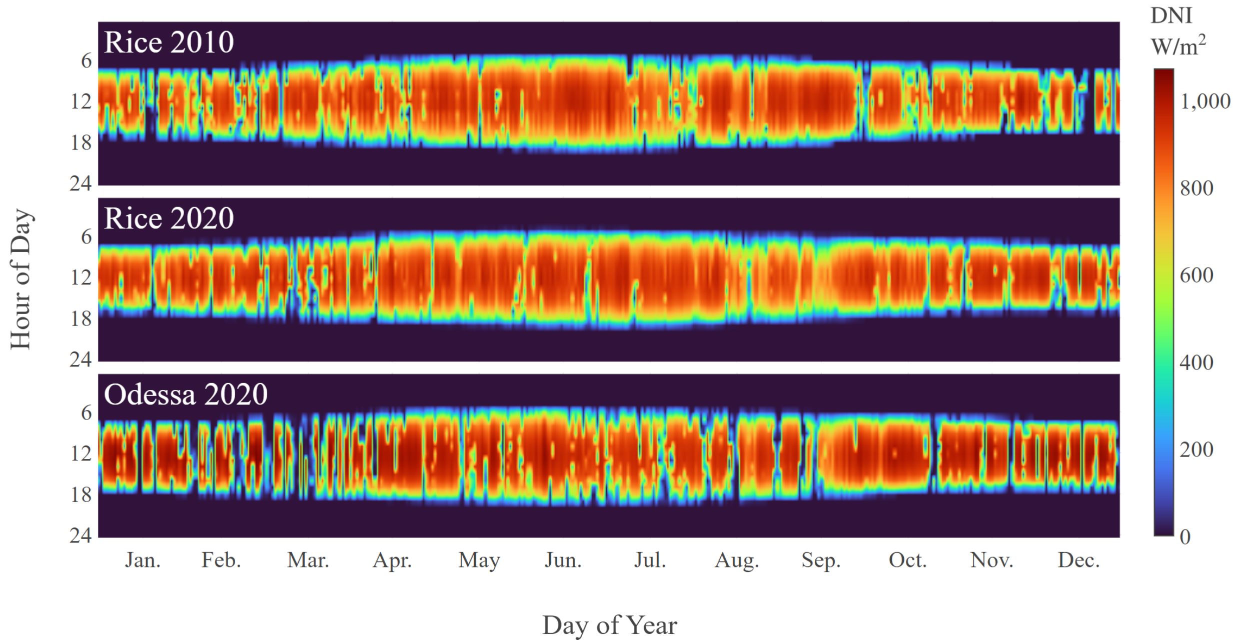

Figure 3.3 Heat map summarizing DNI for the three different cases we study — Rice 2010, Rice 2020, and Odessa 2020.

3.4.3 Pricing

We utilize a publicly available dataset from two different sources — CAISO for Rice and the ERCOT for Odessa, which cover day-ahead hourly prices for both energy and ancillary services, dating back over 10 years. Both the CAISO and ERCOT datasets are ideal because of the ancillary service markets present in both regions. Moreover, both datasets, i.e., ancillary and energy prices from CAISO and ERCOT, are easily accessible.

There is considerable variance in the price of ancillary services. For example in August 2019, due to shortage pricing — a situation in which the system operator does not have adequate capacity to meet both energy and reserves, and, therefore, operating reserves are called upon, the price of spinning reserves reached nearly \$9,000/MWh. While this provides an opportunity for utilities participating in the ancillary service markets to profit from the sale of spinning reserves, such a price spike is rather infrequent; hence, we consider such price points to be outliers. To ensure that our results are not skewed by occasional extremely high prices, we avoid using data from years with very high variability in energy and spinning reserve prices. Even so, variability is often a consistent feature of energy prices, but unlike in 2019, the highest price in our dataset is just above \$2,000/MWh.

In the Rice 2010 case, prices appear mostly constant throughout the day. This is due to the relatively low penetration of renewable energy resources at the time, when compared to 2020. The average price of energy in this case is about \$30, which is in the same range as the other two cases — Rice 2020 and Odessa 2020. The spinning reserve price is equally flat, reflecting low penetration of renewables in the ancillary service market. However, the distribution of prices beyond the average price in the case of Rice 2020 differs from that of Rice 2010. A high level of renewables penetration gives rise to the duck-curve phenomenon in which energy prices are low during the day and high in the evening. The average energy price in the Rice 2020 case is also about \$30/MWh, while the average spinning reserve price is about \$6/MWh. However, prices rose to as high as \$2,000/MWh during the month of August. Finally, in the Odessa 2020 case, while the average energy prices are similar in magnitude to the average prices in Rice 2010 and Rice 2020, the average spinning reserve prices are markedly higher at an average of \$11.61/MWh. In general, spinning reserve prices tend to be higher in Odessa, reaching \$2,000/MWh in the summer months. Figure 3.4 and Figure 3.5 show electricity and spinning reserves prices, respectively. The white traces on the heatmap indicate local sunrise and sunset. Table 3.2 and Table 3.3 show the summary statistics of electricity and spinning reserve prices in the three cases, respectively.

Table 3.2 Summary statistics of normalized, i.e., mean of 1.0, energy prices from the three cases over 8,760 days (i.e., one year).

			Quartile			
Cases	Std. deviation	Minimum	25%	50%	75%	Maximum
Rice 2010	0.30	-0.29	0.82	0.99	1.18	3.09
Rice 2020	1.82	-1.55	0.62	0.86	1.16	47.00
Odessa 2020	1.39	-0.19	0.47	0.67	1.13	66.24

Table 3.3 Summary statistics of normalized, i.e., mean of 1.0, spinning reserve prices from the three cases over 8,760 days (i.e., one year).

			Quartile			
Cases	Std. deviation	Minimum	25%	50%	75%	Maximum
Rice 2010	1.18	0.00	0.28	0.54	1.26	16.32
Rice 2020	5.31	0.02	0.13	0.48	0.70	166.43
Odessa 2020	3.11	0.08	0.30	0.64	1.07	172.30

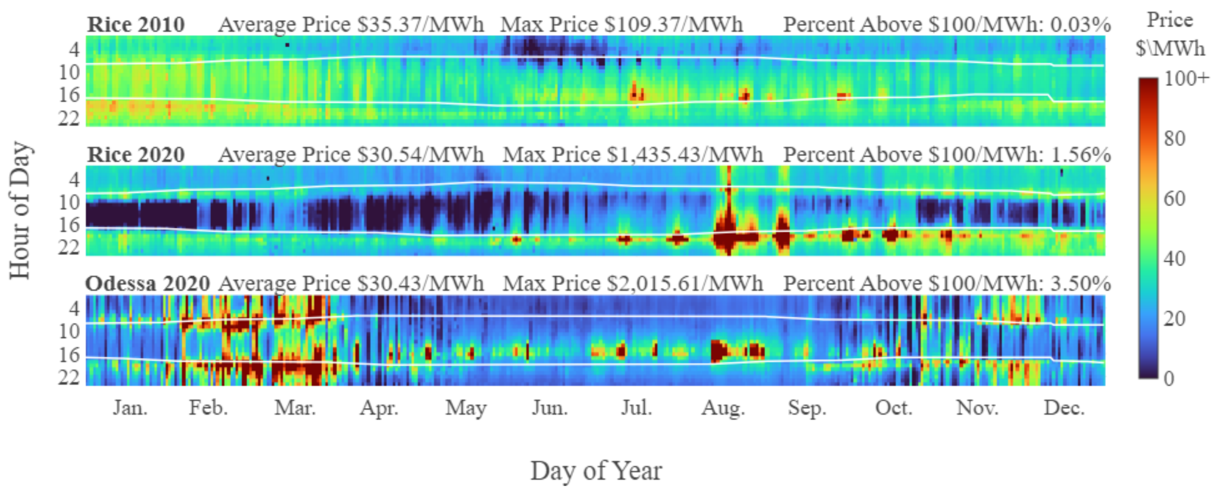

Figure 3.4 Heat map of electricity prices over time for the three cases we study.

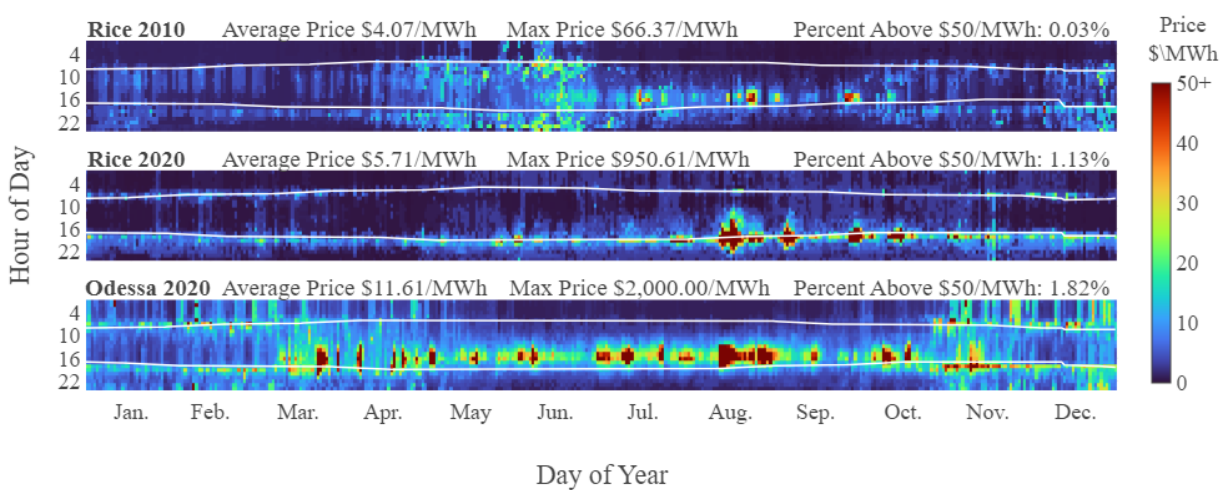

Figure 3.5 Heat map of spinning reserve prices over time for the three cases we study.

3.5 Results

The dispatch optimization model, ($\mathcal{S}'$), is implemented in Pyomo [Bynum et al., 2021] and solved using Gurobi version 9.5 [Gurobi Optimization, 2021]. Hardware architecture consists of a SuperServer 1028GR-TR with a Intel Xeon E5-2620 v4s at 2.1 GHz, 128 GB RAM, 1250 GB SSD, and 3 500GB SSDs, running Ubuntu version 20.04. All instances solve to a 0.1% optimality gap or better; maximum solve time is 22 seconds, and the average is 1.5 seconds.

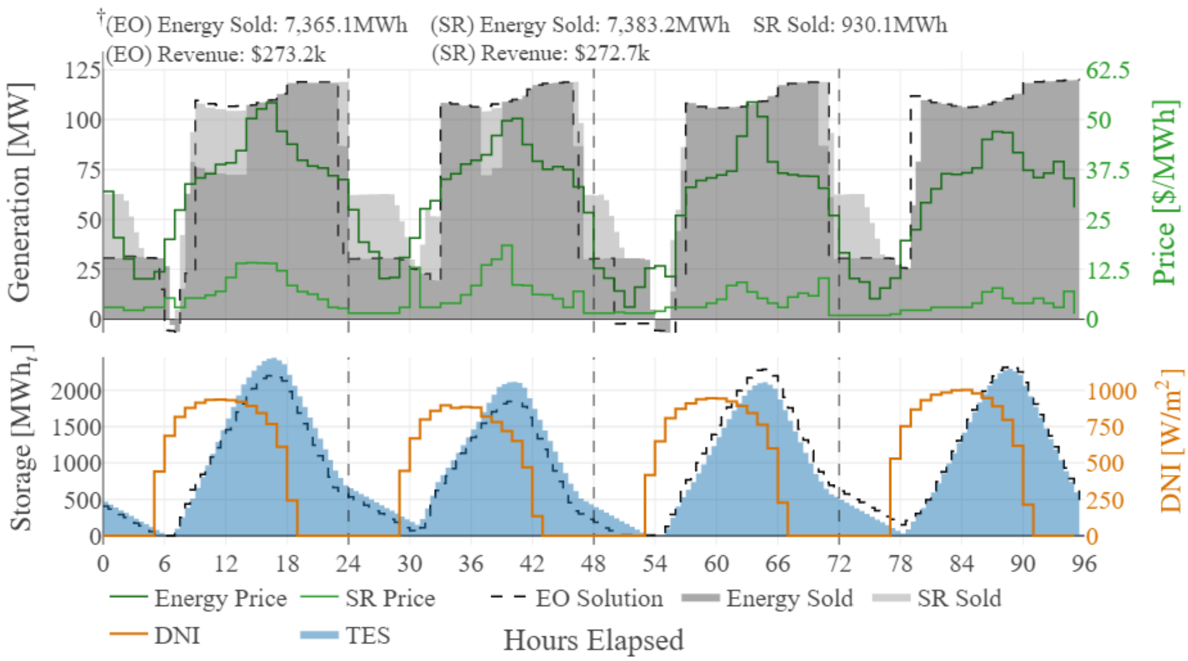

Figure 3.6 The upper half of the graph shows energy and spinning reserves generated for the spinning reserve (SR) case, as well as the energy generated for the energy-only (EO) solution – on the primary axis; and, the energy and spinning reserve prices on the secondary axis. The lower half of the graph shows storage in solid blue for the SR case and storage with the dotted line for the EO case on the primary axis; and, the DNI on the secondary axis.

Using a 72-hour rolling horizon, we solve the three different cases using 2010 and 2020 price data from the CAISO and ERCOT markets over a period of one year with and without spinning reserves. Figure 3.6 shows a three-day time series of prices and sale of energy and spinning reserves on the upper panel, and DNI with storage on the lower panel. The figure embodies the performance of the CSP plant for three randomly selected days from the year-long model, which demonstrates that revenues increase with the sale of spinning reserves. The figure also provides details on the amount of energy sold in both the energy-only and the energy-and-spinning-reserve cases, as well as the three-day total revenue from both cases. While the upper panel shows that both energy and spinning reserve prices have a similar pattern, the lower panel depicts the positive relationship —both move in the same direction — between availability of DNI, denoted by the orange line, and the amount of thermal energy storage, denoted by the blue area.

3.5.1 Rice 2010 Results

In the Rice 2010 case, the CSP plant is profitable in all months of the year in both the energy-only and energy-and-spinning reserves instances in the absence of overhead and financing costs, which are not included in our case study. Operation and maintenance costs are low in both instances, but even lower in the energy-and-spinning reserves instance. Spinning reserve revenue peaks in June, contributing nearly 7% to total revenues. There are significant revenue improvements from reserve sales in all other months as well, which range between 2% and 6% in most months. The Rice 2010 results indicate that revenues and profits are higher when spinning reserves are sold, and correspondingly, operating and maintenance costs are lower owing to less ramping. Specifically, with the inclusion of spinning reserve sales, total annual profit increases from \$15.4 million to \$16.0 million, representing a 3.9% change in profit. The highest revenue in the 2010 case is generated in the month of June, with a total of \$1.905 million in revenue and \$1.90 million in total annual profit. Figure 3.7 shows the classification of profits and revenue for the Rice 2010 case.

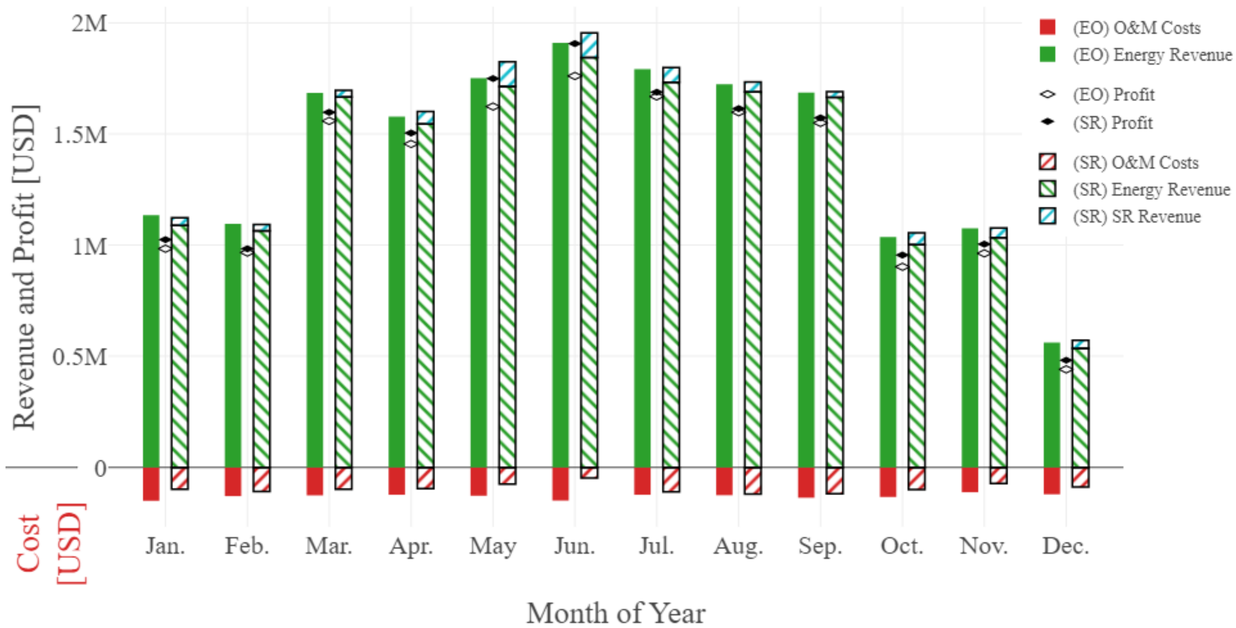

Figure 3.7 Monthly profit components for the Rice 2010 case. Energy only (EO) and energy-and-spinning-reserve (SR) instances are located on the left and right of each month, respectively.

3.5.2 Rice 2020 Results

Similar to the Rice 2010 case, the CSP plant is profitable year-round in the Rice 2020 case. A distinct difference between the two cases is that the contribution of spinning reserves to total revenue of the CSP plant is relatively lower in the winter months, hovering between 1% and 3%. However, this contribution assumes an upward trajectory, starting in June, and reaching a peak of 7.0% in August. The low spinning reserves revenue in the winter months is mostly due to the low heating and cooling loads during that time of the year in Southern California. Similar to the Rice 2010 case, our results in the Rice 2020 case indicate that the inclusion of spinning reserves increases the profitability of a CSP plant. Specifically, in this case, total annual profits increase by nearly 3.5% from \$16.8 million to \$17.4 million. Figure 3.8 shows the classification of profits and revenue for the Rice 2020 case.

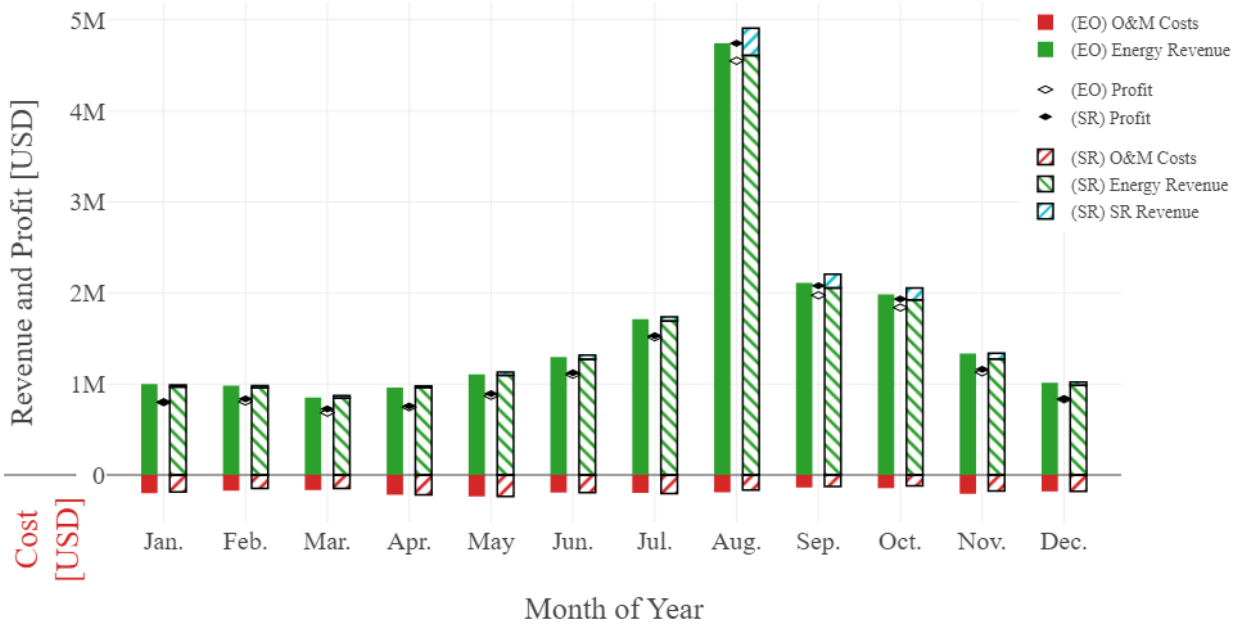

Figure 3.8 Monthly profit components for the Rice 2020 case. Energy only (EO) and energy-and-spinning-reserve (SR) instances are located on the left and right of each month, respectively.

3.5.3 Odessa 2020 Results

The case of Odessa 2020 is similar to that of Rice 2020 regarding renewable energy penetration; however, due to higher spinning reserve prices in the ERCOT market, where we source data for the Odessa 2020 case, we might expect differing results regarding the contribution of spinning reserves to total revenue. As in the first two cases — Rice 2010 and Rice 2020 — net revenues in the CSP plant are positive year-round. A key distinction in the results using ERCOT price data is that reserve sales contribute more substantially to total revenue than in the Rice 2010 and Rice 2020 cases. For example, in August, the month of the year with highest revenue and profits for Odessa 2020, reserve sales constitute 27% of total revenues. Similarly, the contribution of spinning reserves as a percentage of total revenue is also high in several other months of the year: 16% in April and July and 19% in November, whereas the average monthly contribution is about 7.0%. In total, the inclusion of spinning reserves increases total annual profit by over 7.0% from \$14.9 million to \$16.04 million. The results from the Odessa 2020 case strengthen our findings that spinning reserves sales improve the profitability of a CSP Plant. Figure A.1 shows the classification of profits and revenue for the Rice 2020 case.

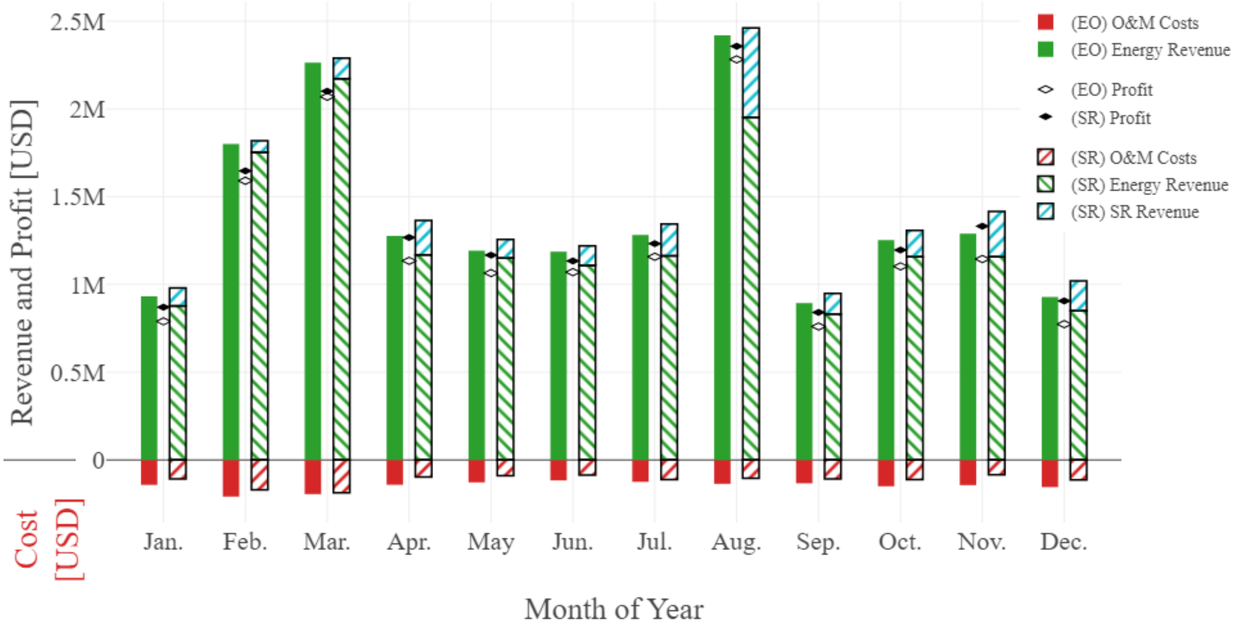

Figure 3.9 Monthly profit components for the Odessa 2020 case. Energy only (EO) and energy-and-spinning-reserve (SR) instances are located on the left and right of each month, respectively.

3.5.4 Results Summary

In summarizing the results from the three cases, we posit that taking the operation and maintenance costs into consideration, the CSP plant is financially viable in both instances of energy-only sales, and energy-and-spinning reserves sales. Consistent with our expectations that spinning reserves can provide an additional value stream, we find that total revenues are higher in the latter instance. Table 3.4 shows the profits and the percentage change in profits between the energy-only instance and energy-and-spinning-reserve instance for all three cases.

Case	Instance	Profits	Relative Profit Increase
Rice 2010	Energy Only	$15,468,346.96	—
	Energy and Spinning Reserves	$16,079,227.40	3.94%
Rice 2020	Energy Only	$16,837,380.72	—
	Energy and Spinning Reserves	$17,417,815.18	3.44%
Odessa 2020	Energy Only	$14,933,362.53	—
	Energy and Spinning Reserves	$16,043,328.63	7.4%

Table 3.4 Summary of profits across the three different cases and instances of services provided

3.6 Conclusions

We incorporate the provision of spinning reserves in a CSP dispatch optimization model with thermal energy storage. Using a 72-hour rolling horizon and price data from CAISO and ERCOT for three different cases, Rice 2010, Rice 2020, and Odessa 2020, we estimate the value proposition of a CSP plant selling spinning reserves in addition to electric energy. More specifically, we use National Renewable Energy Laboratory's System Advisor Model and irradiance data from the National Solar Radiation Database to simulate the dynamics of a CSP plant. While several studies have examined the profitability of a CSP plant, we incorporate profit-maximizing operating decisions that include sales of both energy and spinning reserves. Furthermore, we explore two different markets, demonstrating that profit and revenue contributions associated with spinning reserves can vary across different regions.

Overall, we find that the provision of spinning reserves increases the total revenue and profit of a CSP plant. This finding holds across the three different cases we examine. While the increase in revenues and profits are significant across all three cases, they are most substantial in the Odessa 2020 case due to the relatively higher price of spinning reserves in the ERCOT market. Total profit in the Odessa 2020 case increased by 7% with the addition of spinning reserves, compared to 3% and 4% in the Rice 2020 and 2010 cases, respectively. This significant level of increased profit indicates that the provision of spinning reserves by a CSP plant is viable given the DNI data and market prices used in this study.

In addition to increased profitability, CSP plants participating in ancillary service markets can also serve as a source of grid reliability as the penetration of renewable energy sources continues to grow. Finally, this work demonstrates that given the dispatchability of a CSP plant in contrast to other renewable energy sources, there is untapped potential, increasing its appeal as a renewable energy source of choice. Other ancillary services such as fast frequency response also remain areas in which a CSP plant can participate. Future work could elucidate the contribution of these services to profitability. As efforts towards a clean energy transition intensifies, CSP can be positioned as a major player both in the U.S. and in countries around the world with high solar resource.

3.7 Acknowledgements

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CHAPTER 4

THE ROLE OF MICROGRIDS IN ADVANCING ENERGY EQUITY THROUGH ACCESS AND RESILIENCE

This paper has been accepted in INFORMS TutORials in Operations Research.

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Abstract

Microgrids can play a role in advancing energy equity by (i) extending access to electricity in areas where national grids do not reach, and (ii) enhancing a power system's resilience — the ability to adapt to and rebound from unanticipated shocks — in times of disaster(s) such as extreme weather events or power outages on the centralized grid. In the developing world, access to electricity remains a challenge in the most interior rural areas, where incomes are low and grid connection costs are prohibitive. In both developing and developed economies, the rise of extreme weather events has made the resilience of power systems a concern. Wildfires, for example, are becoming widespread. The United States saw over 71,000 wildfires burn 10 million acres and more than 12,000 buildings in 2017 alone. This specific economic burden — in terms of the impact of wildfires on the U.S. economy — is estimated to be between \$71.1 billion and \$347.8 billion annually. In addition, there is a social cost incurred by vulnerable populations who (i) may be unable to evacuate from the location of a disaster, or (ii) may not have access to mitigating strategies for failed power systems. In this tutorial, we examine the role of microgrids in electricity access and resilience through a systematic review. With respect to electricity access, we investigate the impact of electricity provision through microgrids on outcomes in rural areas of developing countries. For electricity resilience, we assess the effectiveness of microgrids in providing support to power grids in the aftermath of a disaster. We find that microgrids can provide significant benefits in both settings.

4.1 Introduction

The energy equity concept applies to both the developing and the developed world. Energy equity in the developing world focuses on providing energy access to rural and low-income communities. Energy equity in the developed world involves deploying resilient clean energy infrastructure and alleviating energy costs in disadvantaged communities.

In the Global South, most people without access to electricity are based in rural areas, where national grids do not reach. These areas are often sparsely populated, raising concerns about the financial feasibility for utilities. Microgrids can be deployed to improve electricity access in rural areas, and literature is abundant on the role of microgrids in providing energy access to rural and peri-urban areas. However, fewer studies measure the value that microgrids deliver in the medium and long term, both for access and for resilience. For example, only a few energy access studies have used experimental design to measure the contribution of microgrids in job creation, savings in time spent doing household chores, educational attainment and other similar outcomes [Bayer et al., 2020].

Even beyond the Global South, microgrids can be an asset in developed countries such as the United States, as an economical resource for improving grid resilience during extreme weather conditions. In the United States, there are measurable inequities in the share of income that poorer households spend on energy, leading to a trade-off between energy payments and other household expenses. The disproportionate amount expended by low-income households is at the center of energy equity. Cong et al. [2022] formalize a metric, *the energy equity gap*, defined as the difference in inflection temperature — the outdoor temperature at which households decide to turn on cooling systems — between low- and high-income groups. Energy inequities can be exacerbated by unanticipated events that disrupt the central grid operation. Microgrids are considered a potential solution to unexpected outages due to their ability to independently supply backup power (i.e., be connected to or disconnected from the central grid as the need arises). Zhou et al. [2018] argue that microgrids are emerging as the technology of choice for resilience to extreme events.

Understanding the medium- and long-term impacts of microgrids is important in determining whether investments in microgrids are beneficial. We provide these answers, through a systematic review, to two questions. For electricity access: (i) Do microgrids improve economic and non-economic outcomes in rural areas of developing countries? For resilience: (ii) Are microgrids effective in improving resilience of power systems in the aftermath of extreme weather events or other natural disasters? While results on the impact of grid extension on rural electrification are mostly mixed, fewer studies have focused solely on the impact of microgrids or off-grid solutions [Bayer et al., 2020]. This tutorial focuses on rural areas in developing countries when referencing electricity access; however, in general, the findings apply to both developing and developed countries.

Our research straddles both the developing and the developed world. Understanding microgrids' impact on energy access in rural areas worldwide is fundamental for informed policy making to provide affordable, reliable, sustainable and modern energy for all by 2030. Similarly, evaluating the microgrid's role on improving the resiliency of power grids (both in the developed and developing worlds) informs policy decisions to alleviate stress on power systems during extreme events. We review empirical and optimization-based studies on energy resilience during disasters to answer these questions. Empirical papers reviewed in this tutorial describe the causal effects of microgrid deployment on tangible economic and non-economic outcomes, and optimization-based studies illustrate how to optimally size, site, design, and/or dispatch microgrids for improved resiliency during extreme weather events. The remainder of this tutorial is structured as follows: In Section 4.2, we provide background on electricity access, energy resilience and how microgrids can improve outcomes in both cases. Section 4.3 covers data and methods, including the impacts on energy access and the objectives considered in resilience studies. Section 4.4 discuss our findings from the systematic review of access. We conclude with Section 4.5.

4.2 Background on electricity access and energy resilience

There is a long-standing consensus that electricity access opens a vista of opportunities to newly connected areas by providing tangible benefits– ranging from lighting at night to enabling starting small businesses with modest electricity requirements. Several studies document other impacts of rural electrification, including improvement in economic outcomes such as job creation, and gains in educational attainment. Women, particularly, have been found to benefit from time saved on household chores. Yet, findings from recent studies using experimental designs have called into question these long-standing claims of the development due to rural electrification, asserting that such claims might have been overestimated [Burlig and Preonas, 2016, Lee et al., 2020].

While electricity access in the developing world is improving, a sizable number of people, mostly in sub-Saharan Africa and Southeast Asia, still remain without access. In countries where access to electricity has improved significantly, off-grid solutions including mini- and microgrids have been pivotal. Moreover, some gains made in the past few decades have diminished due to the impacts of the COVID-19 pandemic. According to a 2021 World Bank report, the total number of people without access to electricity declined from 1.2 billion in 2010 to 759 million in 2019 [SDG, 2021]. However, the number of people without access in sub-Saharan Africa increased in the past decade. In fact, the report reveals that with current trends, an estimated 660 million people — most of them in sub-Saharan Africa — would still lack access in 2030. This number represents over 50% of sub-Saharan Africa's population, and nearly 10% of the world's. Access in the context of this tutorial merely refers to a connection to a grid, and not to the reliability and affordability of said connection. Certainly, numbers in the report would have been far greater if reliable and affordable access to electricity were considered. As developing countries that are yet to achieve universal access to energy invest in both grid and off-grid solutions, including microgrids, systematic review in this tutorial can help determine where and when investments in microgrids can have the most impact in terms of both economic and non-economic outcomes.

4.2.1 Energy Resilience in the Developed World

Energy resilience remains an unyielding concern in developed countries. Natural disasters, including wildfires, can render the grid vulnerable and result in power outages for extended periods. It is well documented that the resilience of power infrastructure can be compromised by extreme weather conditions and can be costly [Knight and Knight, 2001, Ward, 2013]. Campbell and Lowry [2012] estimate that the annual impact of weather-related outages ranges between $20 and $55 billion. In fact, the resilience of power grids has become a major preoccupation of planners and researchers as climate change continues to induce more natural disasters [Panteli and Mancarella, 2015]. There is a body of work that addresses the impact of climate change on critical infrastructure, including power grids [Karagiannis et al., 2017, Voisin et al., 2020, Kumar et al., 2021]. Current power systems are not resilient in the face of unforeseeable, and even some foreseeable, natural disasters. In the U.S. in particular, rolling outages have resulted from severe weather phenomena such as hurricanes and high winds [Thompson and Calkin, 2011]. As climate change intensifies, there are well-founded concerns that these extreme weather conditions will occur with greater frequency. The critical impacts of these weather events have prompted researchers to study disaster modeling, and how to build resilient power infrastructure. Panteli and Mancarella [2015] review studies on various modeling techniques to assess the resilience of power systems, outlining the challenges in these studies due to the stochastic nature of extreme weather.

The literature on disaster modeling and grid resilience assessment in the United States and European countries is novel but steadily growing. In fact, the risk posed by weather phenomena to the power system is now an emerging and important area of study. While cyber attacks could also undermine power grids (e.g., see [Li et al., 2021]), most threats faced by power grids in developing countries are a result of inclement weather. Therefore, there is the need for backup power systems to be optimized to withstand low-probability, high-impact events. Wang et al. [2020] provide an example of a generic optimization framework for improving grid resilience, and it includes different types of objective functions, resilience scenarios, control methods and resilience-oriented strategies. Various objectives that improve grid resilience include load maximization, cost minimization and frequency stabilization [Zhou et al., 2018]. Other works prioritize load restoration in times of emergencies. The restoration path is often determined by solving an integer-linear program; see, for example, Xu et al. [2016].

4.2.2 Microgrids for Access and Resilience

The planning of a microgrid system requires balancing several objectives, some of which are at odds with each other, given a set of constraints. As a result, different optimization techniques have been applied to solve the planning problem — a task that entails determining the mix of fuels and choice of location, among other logistics. While these techniques vary, some tasks are common to most microgrid design problems. These include power generation mix selection, the siting problem, and scheduling [Gamarra and Guerrero, 2015]. The categorization of these problems is further refined by Akbas et al. [2022], who show in a review of optimization-based solutions for rural electrification, that certain optimization problems appear with a higher frequency: (i) optimal system configuration and unit sizing, (ii) optimal power dispatch strategy, (iii) optimal technology choice, and (iv) optimal network design. Addressing these problems efficiently can optimally increase electricity access in rural areas. Interest in microgrids as a resilience facilitator has been on the rise over the past 10 years due to the increase in major weather events that can cause damage to the grid [Kelly-Pitou et al., 2017]. Microgrids are widely acknowledged to enhance resilience due to their ability to island and independently supply backup power. Similarly, Wang et al. [2020] examine resilience-oriented strategies for dispatching microgrids in times of natural disasters.

Microgrids have been deployed extensively in developing countries' rural areas to help boost access to electricity. Several academic works and technical reports have examined microgrids' role in extending electricity access [Thiam, 2010, Aklin et al., 2017, Moretti et al., 2019]. In these works, microgrids are considered within the context of rural electrification. In terms of the benefits of rural electrification, many studies have identified the role that microgrids can play in electrifying schools in rural areas [Aemro et al., 2020], in environmental sustainability [Ortega-Arriaga et al., 2021], and job creation [Kirubi et al., 2009]. With regard to optimization-based studies to improve energy resilience during disasters, the work can be broadly divided into design optimization [Thomas et al., 2016, Rispoli et al., 2020], microgrid dispatch [Nemati et al., 2018, Moretti et al., 2020], and energy access [Fowlie et al., 2018, Kirchhoff and Strunz, 2019]. The literature on energy resilience also covers the role of microgrids, with applications to healthcare, natural disasters and other extreme weather events [Hussain et al., 2019, Chen et al., 2021].

4.3 Methodology and Data

Our systematic review covers two distinct areas: (i) electricity access, and (ii) energy resilience. Microgrids can improve both and, hence, are included in this review. With respect to the first area, we examine a set of impact assessments — research that evaluates the impact of an intervention (with a focus on microgrids) — directed at rural electrification in the Global South. In the second area, we summarize the findings of optimization-based research on the design and dispatch of microgrids for improving energy resilience during disasters. We also provide a summary of optimization methods covered in the context of energy resilience. Systematic reviews are common in medical research as a way of assembling similar studies for drawing a conclusion based on summarized findings [Collaboration, 2011]. However, systematic reviews have now become a standard in other disciplines as well. Systematic reviews differ inherently from literature reviews. While the latter is not necessarily methodological in the process of collecting and analyzing studies, the former follows a standard, rather than a subjective, approach to selecting reproducible studies using methods or search strings that can be replicated. In short, as the name implies, they follow a systematic way of selecting and analyzing previous studies. For the first area of our review, electricity access, we focus on six outcomes of interest: energy expenditure, business creation, education, health, household income, and household savings. This is similar to Bayer et al. [2020] who study the need for impact evaluation in electricity research. However, we focus solely on microgrids, rather than on the central or national grids.

As a search strategy for articles covering the role of microgrids in expanding access to electricity in the developing world, we use the following string in Google Scholar for articles written since 2000: ("rural electrification") AND "microgrid" AND ("impact" OR "effect" OR "development"). The rationale for using this source is that it usually covers more specific search databases, such as Ebsco, Jstor, ProQuest and Web of Science. Our search produces a total of 6,040 articles, which includes unpublished literature, published articles and articles from non-academic institutions ("gray literature"). To narrow the search to articles that specifically address the impact of microgrids on economic and non-economic outcomes, we expunge a large number of articles on the basis of the title and the abstract. Most of the excluded articles either perform techno-economic analysis of microgrids or explore the financing of microgrids; other studies do not directly investigate the impact of microgrids on energy access. The classification of our search strategy for relevant papers on energy access is shown in Figure 4.1.

Similarly, concerning the role of microgrids in energy resilience in developed countries, we use the following string in Google Scholar for articles written since 2000: ("energy resilience") AND "microgrid" AND "disaster" AND ("multicriteria-optimization" OR "optimization"). This search string produces a total of 355 articles, including gray literature. To the best of the authors' knowledge, this tutorial is the first to conduct a systematic review on the role of microgrids in boosting energy resilience for disaster recovery. The classification of our search strategy for papers on energy resilience is shown in Figure 4.2.

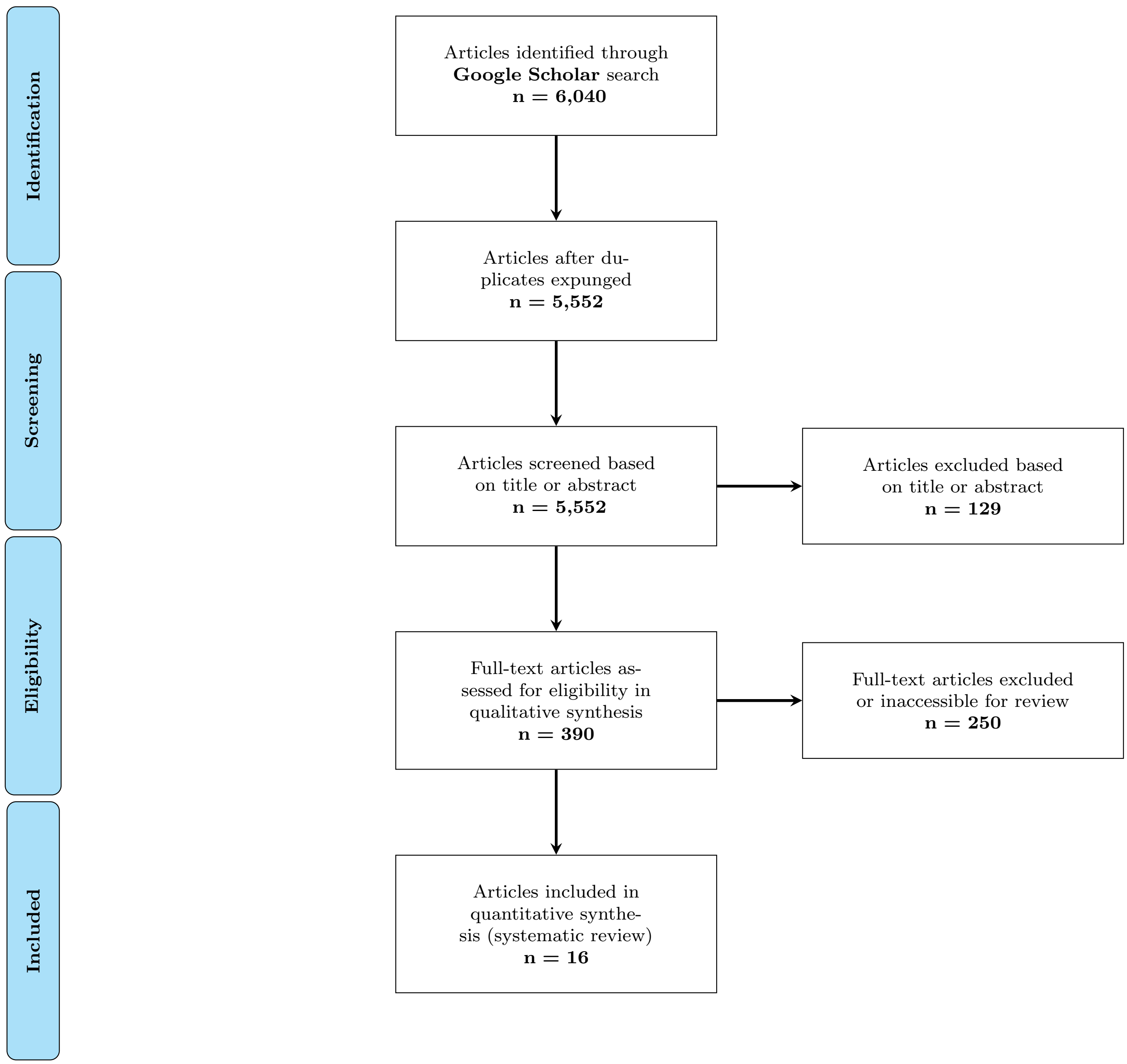

Figure 4.1 PRISMA diagram for review of microgrids and energy access, showing the screening process used in the selection of final reviewed papers.

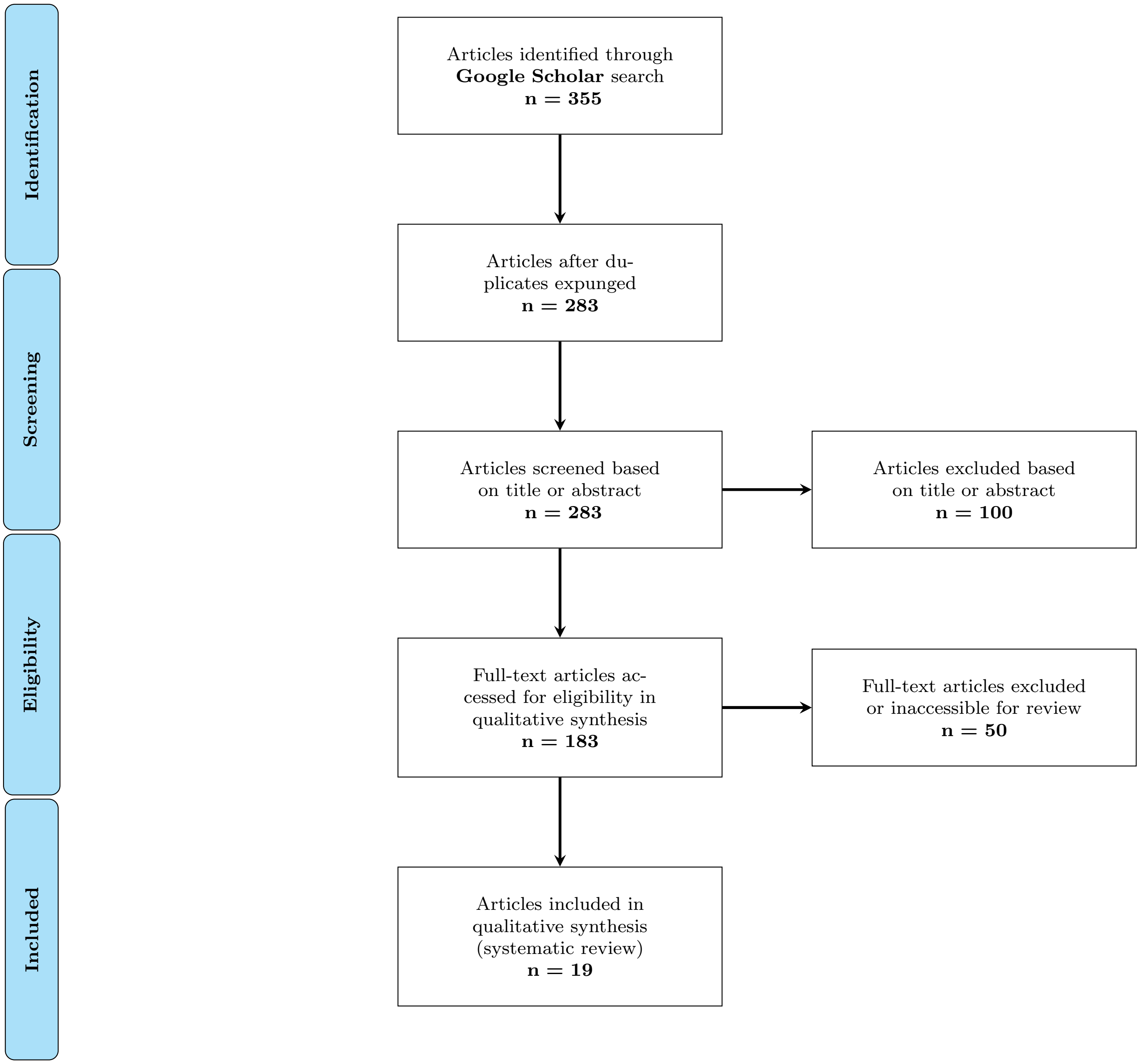

Figure 4.2 PRISMA diagram for review of microgrids for energy resilience showing the screening process used in the selection of final reviewed papers.

4.3.1 Assessed Impacts and Summary of Microgrids on Electricity Access

Overall, with respect to energy access, our final database consists of 16 papers with 43 results – as each of these papers examines multiple outcomes. These studies are selected based on the condition of including a policy implication and quantifiable impacts in areas including household income, education, healthcare, business creation potential, energy expenditures and household savings. These outcomes are the most commonly studied in the energy access literature [Bayer et al., 2020]. Following Bayer et al. [2020], we classify findings from our studies into two categories, namely positive and neutral. Findings coded as positive show some beneficial impacts of microgrids; those coded as neutral show neither positive nor negative impacts of microgrids on the outcomes of interest. The studies we evaluate employ either observational or experimental methods that perform statistical hypothesis testing. We intentionally omit summary studies or those that are purely qualitative. In classifying the findings, we follow the authors' interpretation of the studies we review. The studies that we code as having positive impacts are those with statistically significant results, while those with neutral impacts are those with results that are statistically indistinguishable from zero.

We provide details regarding the six outcomes based on the impact of microgrids on rural electrification. We start with energy expenditure, for which we code an impact as positive (neutral) if it results in an increase (no change). In the energy expenditure category, while Bensch et al. [2011] find an insignificant or neutral effect of microgrids on villages in Rwanda, other studies have found positive impacts in household energy expenditure reductions [Aklin et al., 2015, Agoramoorthy and Hsu, 2009]. In the business creation category, Aevarsdottir et al. [2017] find limited positive impacts of solar lamps in Tanzania. We also assess the impact of microgrids or off-grid solutions on educational and health outcomes. Lighting on its own can enable school children to study at night. Health centers and hospitals also benefit from reliable access to electricity to store drugs. Yet research findings on the impact of electrification on educational outcomes are not unanimous. Furukawa [2014] finds that solar-powered lamps have no significant effect of children's test scores despite increasing their study time by 30 minutes per day. Bensch et al. [2012] also find mixed results — both positive and neutral – on the effect of lighting on test scores. On the contrary, Grimm et al. [2017] find positive impacts of off-grid rural electrification on both educational and health outcomes.

In the household income and household savings categories, electrification has long been thought to provide some poverty-alleviating impacts or benefits. Several research findings also support this thinking. These impacts could occur through the channel of providing people with time to participate in the labor market, reducing expenditures on lighting and fuel, and improving access to mobile phone charging [Bensch et al., 2011, Aevarsdottir et al., 2017]. However, Aklin et al. [2017] find a neutral effect of solar microgrids on household incomes and broader socioeconomic indicators in an experimental study of 1,281 rural households in India.

While these studies focus on different key outcomes, there is overlap as some of these studies report more than one outcome. For example, while Aevarsdottir et al. [2017] focus on the main outcome of energy expenditure, their study also shows the impact of off-grid electrification on other outcomes such as education, business creation potential, and household income. Similarly, while the focus of Kudo et al. [2019] is the impact of off-grid solutions on health outcomes, their study also shows that solar lamps reduce fuel expenditure.

4.3.2 Assessed Objectives of Microgrids for Energy Resilience

For a systematic review of the role of microgrids on energy resilience during disaster events, we review 19 papers that address the role of microgrids in providing energy resilience during a disaster. The need for resilience in power systems is well-acknowledged. Rising temperature and climate-induced disasters pose threats to power systems in the United States and globally. There is ample documentation of the economic costs and physical damage resulting from high-impact, low-probability events [Goss et al., 2020, Palaiologou et al., 2019]. Lower-income residents have a higher chance of exposure to outages in the wake of a disaster as they are less likely to have established mitigation programs to help absorb resulting loss. Microgrids can serve to provide energy equity in such settings to low-income households by ensuring continued energy coverage.

For widespread microgrid deployment to improve resilience, individual microgrids should each provide additional resilience at low additional cost. The studies we review are unanimous in their findings across these two main objectives of maximizing resilience and minimizing life cycle costs of microgrids. Unlike the effects related to the impact of microgrids on energy access, all the studies in this section report some positive effect of microgrids on energy resilience. Some of these studies examine both objectives — maximizing resilience and minimizing costs — simultaneously [Younesi et al., 2021, Masrur et al., 2021]. Together, these studies show that microgrids effectively maximize resilience while minimizing additional cost (for added resilience).

The reviewed studies quantify these objectives through various means. Therefore, to summarize the goal of each study, we document their key findings in Table 4.1. For example, Younesi et al. [2021] define a custom resilience metric incorporating corrective action timeliness, fragility, restoration efficiency, microgrid voltage, and lost load. At least nine of the reviewed studies define microgrid-related disaster resilience by the number of hours or days in which microgrids can increase outage survival in a given setting. A disaster's major impact on power systems is the disruption in power supply; hence, a resilient power system can withstand an unforeseen event and prevent outages or restore power supply swiftly after an outage, without significant economic losses. Anderson et al. [2017] find that by providing renewable energy through photovoltaic and battery energy storage system technologies in a hybrid microgrid, the amount of time a service center could survive an outage increases from 1.7 days to 3.5 days. Similarly, Masrur et al. [2021] show that their proposed microgrid design, when optimally dispatching renewable energy, can save about $73,000 (US dollars) on average and withstand 718 hours of outage over a period of 25 years.

Table 4.1: Summary of Optimization-based Studies

Author	**Methodology**	**Objective**	**Findings**
Alqahtani et al. [2018]	MILP	Min costs	Identified most important locations for microgrids.
Anderson et al. [2017]	(REopt) MILP	Max resiliency	Increased outage survival days from 1.7 days to 3.5 days.
Anderson [2020]	MILP	Min costs	Achieved 8% higher resilience (invulnerability and recovery) for equivalent costs.
Barbar [2019]	LP	Min costs	Found additional line hardening to be optimal for urban networks, and generation relocation and resizing to be optimal for rural networks.
Borghei and Ghassemi [2020]	MO-MILP	Max resiliency	Restored critical loads in 20 minutes.
Chen et al. [2016]	MILP	Max resiliency	Microgrids formed to power highest-priority loads.
Cook et al. [2020]	(REopt) MILP	Max resiliency	Continued supplying power for up to 25 more days with additional savings of $13,000 in 3 cases.
Gaikwad et al. [2021]	MO-MILP	Max resiliency	Powered home refrigerator for six additional days during 7-day power outage.
Gilani et al. [2020]	MILP	Max resiliency	Protected 33% of the network loads from an outage.
Hervás-Zaragoza et al.	(REopt) MILP	Max resiliency	Met 60% of hospital power needs during 24-hour outage with additional $456,000.
Lagrange et al. [2020]	(REopt) MILP	Min cost	Powered hospital microgrid through 8-24 hour outage with additional savings of $440,000 over 20 years.
Lau et al. [2018]	MILP	Max resiliency	Supplied power to scaled-down low-voltage subnetwork and full low-voltage network through 6-hour outage.
Marqusee et al. [2021]	(REopt) MILP	Max resiliency	Improved survival probability for 14-day outage with additional savings up to $12,000,000 in 3 cases.

Table 4.1 Continued

Author	Methodology	Objective	Findings
Masrur et al. [2021]	MO-MILP	Min costs	Saved more than $73,000 over 25 years.
		Max resiliency	Increased outage survival hours by 718 over a 25-year period.
Reyes-Ascanio et al. [2021]	(REopt) MILP	Max resiliency	Supplied power for a mean length of 61 hours during outages.
Rosales-Asensio et al. [2019]	(REopt) MILP	Min cost	Achieved cost savings of $\$112,410$ over a period of 20 years.
Wang and Wang [2015]	MINLP	Min cost	Powered all affected loads for 1.5-hour outage.
Younesi et al. [2021]	MO-MILP	Max resiliency	Increased custom resilience metric by 16%.
		Min cost	Reduced cost of microgrids operation by 28%.
Yuan et al. [2020]	RO	Max resiliency	Reduced load shedding in a hurricane.

Table 4.1 This table shows the selection of papers based on the search criteria defined in Figure 4.2. The optimization method used in each of the papers and their key findings are summarized. Note that some studies in this collection use a two-level optimization approach, and hence address both the maximization of resiliency and minimization of cost objectives. LP: Linear Program; (MO)-MI(N)LP: (Multi-Objective) Mixed-integer Linear (Non-linear) Program; REopt: Renewable Energy Optimization; RO: Robust Optimization.

Balancing the trade-off between improved power system resilience and additional cost is another vital consideration as more microgrids are being deployed. Younesi et al. [2021] show that under different scenarios, depending on the assumed impact of a disaster, microgrids can increase a power system's resilience by up to 70%; however, the resulting increase in cost may be as high as 25%. Other studies have proposed ways to choose an optimal microgrid design that maximizes resilience while minimizing costs [Younesi et al., 2021, Anderson, 2020].

The studies we review cover the role of microgrids in improving the energy resilience of hospitals, for uninterrupted delivery of health services [Lagrange et al., 2020]; military bases, for mission assurance [Anderson, 2020]; and, service centers, for efficient service delivery [Anderson et al., 2017]. Table 4.1 provides the optimization methods used in these studies. A summary of the results from the reviewed papers is further analyzed in Section 4.4 through 4.4.2.

4.4 Results and Discussion

We now discuss and summarize results based on findings suggested by the authors of the reviewed papers. Some findings overlap across the outcomes of interest, for both energy access and energy resilience categories.

4.4.1 Discussion of Observational Versus Experimental Methods

The studies we examine for the role of microgrids in energy access can be broadly classified into two categories — observational and experimental. Observational studies rely on surveys or other secondary means to collect data on variables of interest. By contrast, experimental studies use a random assignment, where one group receives some intervention (treatment group), but another similar group does not (control group), to collect the same variables of interest. Overall, we assess six outcomes from a total of 16 studies with 43 results in the energy access section. The number of results is greater than the number of studies because various studies examine multiple outcomes of interest. While it is a common belief that electricity access provides a range of benefits– from business creation potential to reduction in energy expenditure and improvement in educational outcomes, the results from our review are mixed, ranging from positive to neutral. The experimental studies find fewer positive results relative to the observational studies.
Figure 4.3 compares the number of positive and neutral results from the studies on energy access. For the experimental studies, 13 out of a total of 25 experimental studies (52%) are positive (i.e., find microgrids beneficial). In the case of the observational studies, studies that find microgrids to have a positive impact are relatively higher in comparison to neutral at 67%.

Additional results for each outcome are shown in Figure 4.4. In the energy expenditure category, results with positive outcomes exceed neutral outcomes across both observational and experimental studies. However, in the business creation category, we review only two experimental studies, one of which has a positive result. In the education category, we find the highest number of positive results from observational studies; however, experimental studies in same category yield more neutral than positive results. In the health category, both results from observational studies are positive but only one out of the two results from the experimental studies is positive. Similarly, in the household income category, all results from observational studies are positive, but only one of three results from experimental studies is positive. Results are also equally split between positive and neutral outcomes in the household savings category.

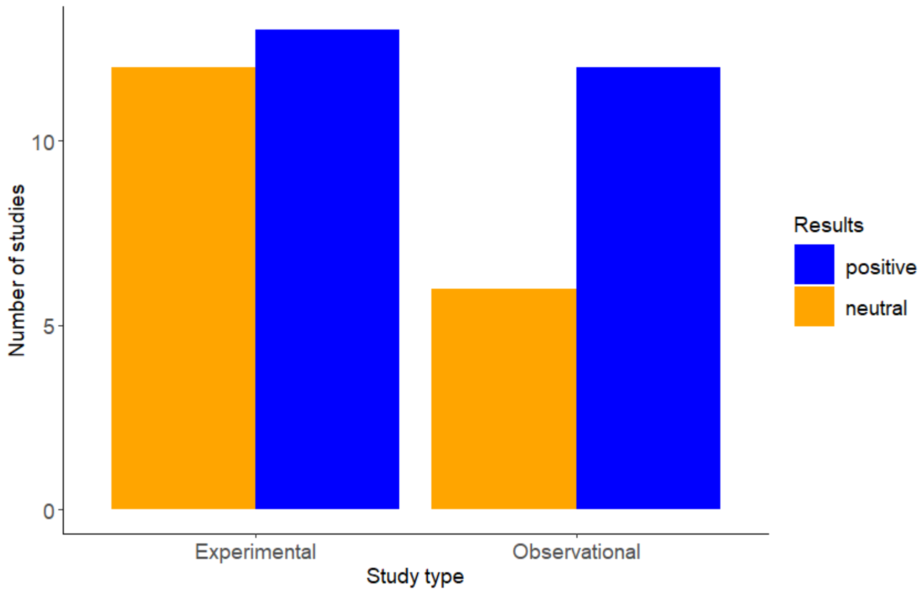

Figure 4.3 This figure shows the total number of experimental and observational studies reviewed in the energy access section. The total number of positive and negative results are indicated by the legend.

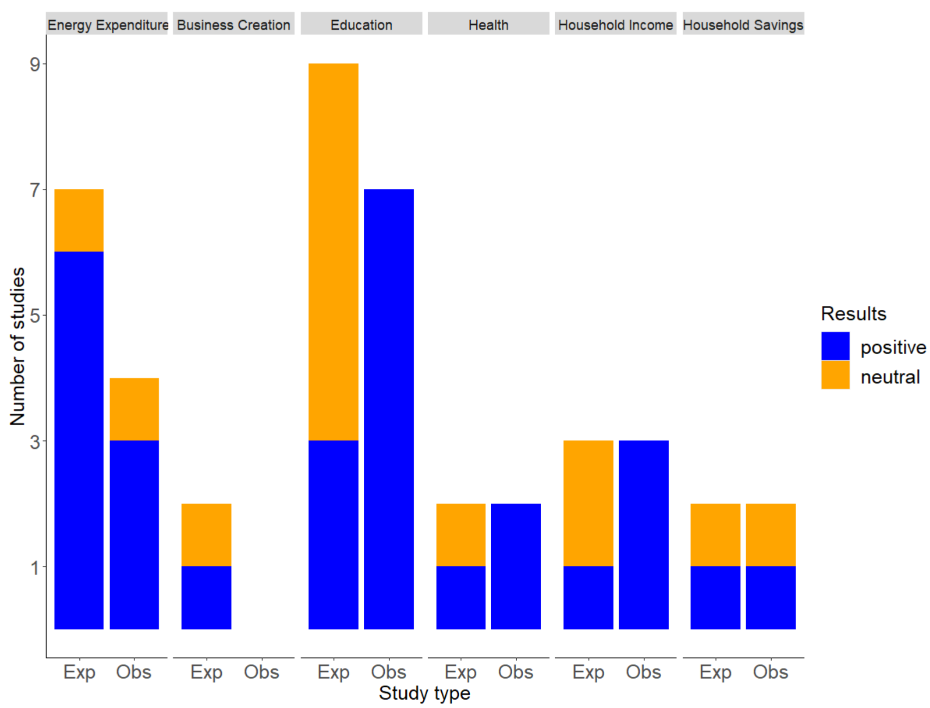

Figure 4.4 This figure shows the breakdown of results across the six different outcomes that we assess. In the business category, we review only experimental studies as we find no observational studies examining business creation outcome. The total number of positive results is shown in blue, and total number of neutral results in yellow. Exp = Experimental study, Obs = Observational study.

4.4.2 Discussion of Optimization-based Studies on Energy Resilience

The studies we examine on the role of microgrids in energy resilience are based on optimization methods, which broadly target two categories of objectives (in relation to microgrid design and operation) — maximizing resilience or minimizing cost for increasing resilience. We find that the studies in the first category most commonly define increased resilience as an increase in the length of time that power is supplied to loads that would otherwise face outages; six studies focus on this. Four studies in that first category maximize the load protected from outages, and the remaining studies measure either response time to restore critical loads, or some other resilience metric. In the second category of cost minimization, we review three studies, which compare the calculated cost of the baseline power system to that of the microgrid-enhanced power system, over the anticipated lifetime of the microgrid equipment.

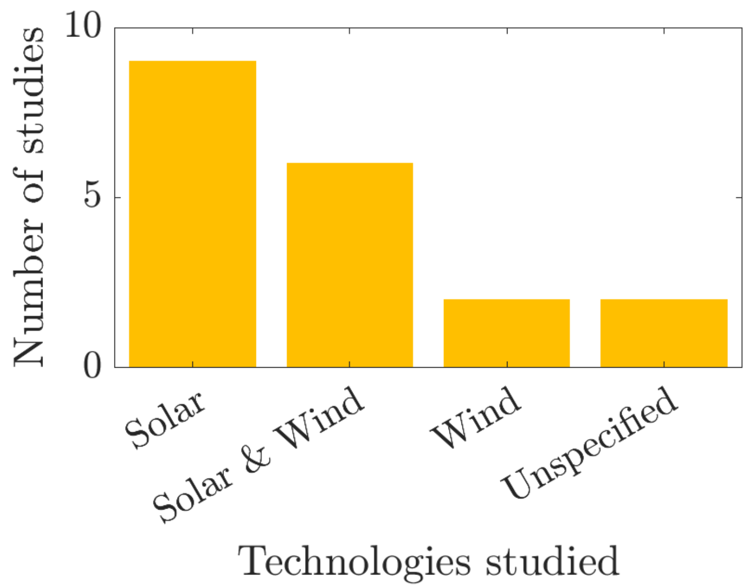

Figure 4.5 Number of studies in the energy resilience section that specify solar or wind technologies as a source of energy in the microgrids.

Out of the 19 resilience studies outlined in Table 4.1, 17 papers either include solar photovoltaics or a wind turbine as possible technologies: nine studies include solar photovoltaics, six include both wind and solar, and two include only wind turbines. Of those same 17, 15 also include diesel or some dispatchable generation. Only two papers do not specify the technology incorporated into the microgrid. Figure 4.5 shows the distribution of the different technologies included. A metric of resilience that many of these studies do not quantify is the value of additional power provided to loads during outages, originating from the concept of "Value of Lost Load" (VoLL). While two studies directly incorporate VoLL into their measure of the benefits of resilience, three studies specifically reference the potential value of incorporating VoLL while acknowledging their omission of the measure due to the difficulty in quantifying it. Still, one study explicitly argues against including VoLL when evaluating microgrids whose non-outage operations provide a return on investment [Cook et al., 2020]. Related to the idea of VoLL, two studies include prioritization of loads when planning microgrid coverage.

4.5 Conclusion and Future Work

We review a total of 35 papers, addressing both the role of microgrids on improving energy access (16 papers) and resilience (19 papers). These papers are selected following a reproducible systematic approach. Regarding energy access, we focus on the channels through which microgrids impact economic and non-economic outcomes. These six outcomes, which are the most studied in the energy access literature, include: energy expenditure, business creation, education, health, household income and household savings. [Bayer et al., 2020]. With respect to energy access, we divided the reviewed papers into two categories — observational and experimental studies. The results from these studies are mixed. However, across the outcomes that we examined, we find that reviewed papers report more positive than neutral results. Out of the 43 results reported, 29 are positive, i.e., demonstrate some statistically significant effect of a microgrid installation on one of the outcomes of interest. There are also some nuances in the results between the two categories of studies. Specifically, observational studies report more positive outcomes than experimental ones. In fact, 88% of the results from observational studies are positive, but only 50% from experimental studies are positive. While we do not rank the accuracy of either type of study, experimental studies have become more widely accepted as the gold standard in empirical research [Wozny et al., 2018].

With respect to energy resilience, while results emanating from reviewed papers are interpreted differently than in the energy access section, we conclude that overall, microgrids are essential and effective in providing resilience to the grid in the aftermath of a disaster. The need for resilience is present in several settings, including healthcare facilities, office buildings and other critical service centers. Microgrids are particularly attractive as an option for bolstering grid resilience largely due to their islanding capability. The papers we review employ different optimization methods to quantify improvement in energy resilience, most notably mixed-integer linear programming. Using scenarios derived from disaster outbreaks and potential impacts on the grid, these works identify that microgrids of various designs can help mitigate the impact. In some cases, microgrids can facilitate the restoration of power faster than the business-as-usual scenario; in others, they can increase the outage survival hours significantly. However, there are often trade-offs between increasing resilience and cost considerations. Findings from some of the reviewed studies indicate that the associated costs of building microgrids for power system resilience may not be justified.

But, such findings are in the minority. Findings from a greater number of the reviewed studies show that microgrids could maximize resilience while minimizing costs relative to the business-as-usual scenario.

Overall, the results from both energy access and resilience offer some important lessons. First, the results from energy access indicate a need for an increased use of experimental designs in empirical research. More so, the mixed results that we see indicate that the impact of microgrids on energy access could vary across different countries. While an investment in a microgrid project can certainly increase access to energy for populations without it, it does not imply that such access, vital as it may be, will result in improving economic outcomes. Therefore, it is important for policy makers and investors in microgrids to consider various country-specific conditions to maximize the desired outcomes of a microgrid project.

In our review of whether microgrids improve the energy resilience during disaster events, many questions emerge. One such question is: how does one determine the value of outage protection when considering a microgrid? Additionally, some of the reviewed studies simply propose techniques for ensuring coverage of loads in the network, with no consideration for the underlying benefit that this brings to the consumers of that load. The "Value of Lost Load" concept covered by many studies shows potential to address this gap. It is important for microgrid policy makers and investors to have a clear notion of what the benefits of a disaster-resilient microgrid are, as they decide how to move forward with such projects.

4.6 Acknowledgment

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CHAPTER 5

FIRM PRODUCTIVITY AND OUTAGES IN TUNISIA

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Abstract

Firms in middle-income countries with universal electrification also experience outages, albeit infrequently. This paper estimates the impact of power outage on firm performance in Tunisia, a country with a 100% rate of electrification using matching methods. We estimate both sample average treatment effect and sample average treatment effect on the treated. Our results show that outages have no discernable marginal effect on firm productivity among affected firms. This finding suggests that Tunisia has made massive investments in electrification on the path to universal electrification, and that firms can adapt in the presence of any remaining reliability issues.

5.1 Introduction

Tunisia, like several other middle-income countries, has since attained a 100% rate of electrification. Yet, firms in the country still report experiencing power outages, which are as high as thirty per year. While these outages are relatively fewer than in sub-Saharan Africa, there is a dearth of studies examining their impact[Cole et al., 2018]. This paper examines the question, *Does Universal Electrification Shield Firms from Productivity Loss?* by focusing on a single country with universal access to electricity. To estimate the impact of power outages on firm productivity in Tunisia, we use a matching, a quasi-experimental approach, which constructs a control group by matching each treated unit with a non-treated unit of similar characteristics. With this approach, we are able to derive causal estimates of the effect of power outages.

Power outages are arguably more pervasive in sub-Saharan African Countries and other low-electrification, developing countries, where they constitute an obstacle to firm productivity. In these countries, several studies have quantified the negative impacts of outages [Allcott et al., 2016, Cole et al., 2018, Mensah, 2018]. Allcott et al. [2016] estimate that due to power outages, Indian manufacturers suffer a mere 1.5% loss in productivity, although revenues reduce by a greater percentage. Fried and Lagakos [2020], in a departure from empirical modelling, build a dynamic macroeconomic model to analytically show how power outages affect firm productivity in sub-Saharan Africa. They argue that empirical models describe only short-run partial equilibrium effects, which may be modest. However, longrun

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general-equilibrium effects from their analytical model include an increase in productivity per worker from eradicating power outages. Other studies have focused on how electrification can boost productivity and employment. For example, Dinkelman [2011] focuses on the effect of grid expansion in rural South Africa, showing that female employment increases in the wake of electrification through the channel of freeing up time spent in home labor. Similarly, Chakravorty et al. [2014] investigates the effect of electricity quality on rural employment. They find that while connection to the grid provides a modest increase to rural household incomes, a high quality provision of electricity, which implies fewer outage contributes substantially to incomes.

With low rates of electrification, it is arguable that firms that rely on electric power to run business are likely to be affected by irregular supply of power, which is characteristic of many developing countries. However, in other middle-income countries with high rate of electrification but imperfect reliability, an important question is whether outages have any discernable impact on firm productivity. To the best of our knowledge, no study has yet to focus on electricity reliability in universally-electrified developing countries. Attaining universal electrification has been described as a milestone for low-electrification countries; hence, countries with a 100% rate of electrification are often assumed to have attained the pinnacle of electrification goals. It is possible for universal electrified countries to have very high reliability, it is also plausible to suffer from poor reliability. In the case of Tunisia, while reliability is not poor, it is not perfect either.

We employ a cross-sectional dataset from the World Bank Enterprise Survey, covering over $1,000$ firms in Tunisia between 2013 and 2020 to estimate the impact of power outages on firm productivity. We use total annual sales, described simply as sales, as our dependent variable and a binary variable indicating whether a firm experiences outages or not as the treatment variable. Other covariates include past sales of firms, age of firm, size of firms and number of permanent workers. A major problem with OLS estimates is that they are likely to suffer from a selection bias problem resulting from a concentration of low-sales firms in localities with more frequent outages. As we observe in our dataset, the percentage of firms experience outages in the North West region of the country — the poorest region — is nearly 60%, whereas, the average for the other regions of the country is 20%. To address this selection bias, we use matching, which provides a compliment to regression analysis, and in this case a more efficient way to estimate causal effects. While we do not observe the income levels in the region, we observe the past sales of all firms, which serves as a good proxy for the income levels of the region. We find that outages, the treatment variable, has no average effect on firm productivity across the different matching specifications, including nearest-neighbor matching, propensity score matching and multivariate-distance kernel matching. We estimate both sample average treatment effect (SATE) and sample average treatment effect on the treated (SATET)

Our contribution lies in identifying the causal impacts of outages in a universally electrified country, Tunisia. This finding may also be applicable to other high-electrification countries with similar characteristics and outages. But we make no general claim about the external validity of this work. The rest of this paper is structured as follows: Section 5.2 details source of data and empirical approach. Results are discussed in Section 5.3. Section 5.4 concludes.

5.2 Empirical

This paper estimates the impact of outages on firm productivity in Tunisia. The ideal dataset for this endeavor is one that is nationally representative and provides information on a wide range of firm attitudes, challenges and performance indicators as well as a community-level location of firms in the Country.

The WBES is a nationally representative survey, which provides information on firms' attitudes, attributes, access to infrastructure, and obstacles that firms face in the day-today running of business. The survey adopts a two-stage stratified random sampling strategy. Top managers and business owners in 139 countries are interviewed face-to-face to gather this information. However, the dataset does not include the community-level location of firms. The survey used in this study was carried out between 2013 and 2020. We also use Gross Domestic (GDP) Deflator and Purchasing Power Parity (PPP) from the World Development indicators and International Monetary Fund to covert the Tunisian currency into 2010 US dollars.

The variables we use in this study are constructed from self-reported figures, which are prone to the usual errors associated with self-reporting. Reported figures tend to be exaggerated or underestimated for various reasons. however, the recall bias associated with our treatment variable is arguably minimal as respondents can easily recall whether they have experienced outages in the past year or not. In order to reduce the impact of outliers in the other variables, we log-transform values of all variables, and return as missing those values that are three standard deviations away from the mean.[22]

The firms in this study are divided into three different categories — small, medium and large, constituting 36%, 40% and 24%, respectively. Large firms have over 100 employees, while medium and small firms have between 20 and 99, and below 20 employees, respectively. By industry classification, manufacturing constitutes 60% of all firms, while retail are services make up 10 and 32%, respectively.

5.2.1 Empirical Approach — Methods

Outages in most developing countries are arguably not random. In that case, estimating their impact using Ordinary Least Squares regression results in biased and inconsistent results arising from the

[22]The log-transformation is performed only to remove outliers, but control variables are not logged in the regressions. This follows the recommendations of the Enterprise Analysis Unit of the World Bank. See https://www.enterprisesurveys.org/en/methodology

endogeneity problems. Matching estimators have been widely applied in non-experimental settings to derive causal effect of a treatment by matching non-treatment units with treatment units based on similarities of observables. In this study, while we do not observe the income levels of the different regions profiled, we observe the past sales of all firms in all regions, which provides a good approximation to income. Matching also has the advantage of not requiring a functional form as is the case with a regression. In what follows, we lay out the matching framework, based on the potential outcomes framework.

$$\text{Potential Outcome} = \begin{cases} Y_{1i} & \text{if } T_i = 1 \\ Y_{0i} & \text{if } T_i = 0 \end{cases} \tag{5.1}$$

where Y_{1i} represents the sales of firm i when experiencing outage, and Y_{0i}, the sale of firm i in the absence of outage. $T = 1$ indicates experiencing outage, while $T = 0$ indicates not experiencing outages. We seek to estimate the average treatment effect and average treatment effect on the treated using the following equations (5.2) and (5.3), respectively. Since we use observational data in this study and cannot observe the both potential outcomes as in the case of a randomized experiment, matching can be applied to make the outcome and treatment independent by conditioning them on observed covariates X_i. A key assumption is the Stable Unit Treatment Values Assumption (SUTVA), which requires that conditional on covariates treatment assignment should be independent of outcomes Y_{1i} and Y_{0i}. In non-experimental cases, this assumption is often violated. However, as Guo and Fraser [2014] argues, this assumption can be relaxed to estimate average treatment effect on the treated using propensity score matching and other matching model and other matching estimators. The second assumption requires that the probability of treatment should neither be zero nor one. With reference to this study, this implies that if all firms with a similar characteristics received the treatment, i.e., experienced outages, there should be no firms with similar characteristics in the non-treatment group.

$$\delta = E[Y_{1i} - Y_{0i}] \tag{5.2}$$

$$\tau = E[Y_{1i} - Y_{0i} | T_i = 1] \tag{5.3}$$

5.2.2 Propensity Sore Matching (PSM)

Matching on propensity scores relies on a seminal work by Rosenbaum and Rubin [1983], which creates an index that combines information on covariates, X_i, by find untreated observations with similar characteristics for constructing a counterfactual. This index is the propensity score, which is computed as follows:

$$P(X) = Pr(T_i = 1 | X_i) \tag{5.4}$$

Given $P(X)$, SATE and SATET are defined as:

$$\text{SATE} = E[E\{Y_{1i}|T_i = 1, P(X_i)\} - E\{Y_{0i}|T_i = 1, P(X_i)\}] \tag{5.5}$$

$$\text{SATET} = E[E\{Y_{1i}|T_i = 1, P(X_i)\} - E\{Y_{0i}|T_i = 1, P(X_i)\}|T_i = 1] \tag{5.6}$$

5.2.3 Nearest Neighbor Matching

The nearest neighbor matching uses a geometrically defined algorithm to pair or match a given point with another 'closest' point. This matching is done between between pairs of observations in the treatment and control groups. The algorithm finds an untreated observation with the closest value of the propensity score which receives a weight of 1, while all other observations are assigned zero weight. This can be done with or without a replacement [Abadie et al., 2002].

5.2.4 Kernel Matching

This approach uses averages of untreated observations such that more weight is assigned to untreated observations that are closer or with smaller distances, using kernel functions such as the Epanechnikov kernel. The kernel may or may not assign positive weight to the entire range [0,1] [Becker and Ichino, 2002].

Table 5.1 Summary Statistics

Variable	Obs.	Mean	Std. Dev	Min	Max
Sales (USD)	1,101	120861.1	400395.1	133.2183	5,904,959
Log Sales	1,101	9.97834	1.773395	4.891989	15.5913
Past Sales (USD)	1,006	108,449.6	449,914.5	8.038507	10,000,000
Log Past Sales	1,007	14.58	1.719	3.689	20.541
Permanent Workers	1,101	95.701	219.888	1	3400
Age of Firm	1,096	26.674	14.426	3	115
Outages	8,348	.264	.441	0	1
Size of Firms	Frequency		Percent		Cumulative
Small	395		35.88		36.88
Medium	445		40.42		76.29
Large	261		23.71		100
Total	8,348		100.00		
Size of Locality	Frequency		Percent		Cumulative
Biggest City	119		10.81		10.81
Bigger City	65		5.72		16.53
Medium City	275		24.98		41.51
Small City	378		34.33		75.84
Small City	266		24.16		100
Total	1,101		100.00		

Notes: This table provides summary statistics of all key variables in this paper. Sales value are expressed in purchasing power parity 2010 dollars.

5.3 Results

In this section, we provide discussion on treatment effects, balancing and overlap diagnostics using different estimators. Figure 5.1 shows the the standardized differences in both the treated and untreated groups. This information is also detailed in Table 5.2. In Table 5.3, we detail both the sample average treatment effect and sample average treatment effect on the treated. The matched sample results show that both the multivariate-distance kernel matching and nearest neighbour matching produces good matches. This is evident in the standardized differences, i.e., the difference in standard deviation which are very close to zero and the variances, which are close to one, the theoretically accepted threshold

5.3.1 Treatment Effects

Matching on observables provides an opportunity to estimate the causal effects of power outages on firms in Tunisia. Estimating causal effects in non-experimental settings is often fraught with problems arising chiefly from selection bias. In this study, our dataset does not include community-level location of firms, but we observe that the North West region of Tunisia has the highest percentage of firms experiencing outages. This same region is the poorest in all of Tunisia. To approximate the income levels of the region, we match on past sales, which provides a good indication of the economy of the different regions, among other covariates. Table 5.3 shows the SATE and SATET using propensity score matching, kernel matching and nearest neighbour matching. Except in two cases where the coefficients are negative in two cases using SATE, all other coefficients are positive and statistically insignificant. These results indicate that power outages have no effect on firms in Tunisia. The results are plausible, given infrequent outages in the country, and its long history of universal electrification.

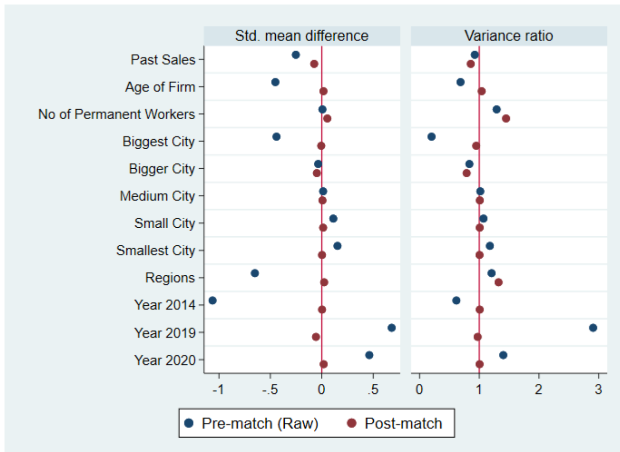

Figure 5.1 This figure shows the standardized differences in the mean values of each covariates as well as the variance ration. The blue dot represents the difference in mean in the pre-match (raw) observation, while the red dot represents the differences in mean post-match using propensity-score kernel matching.

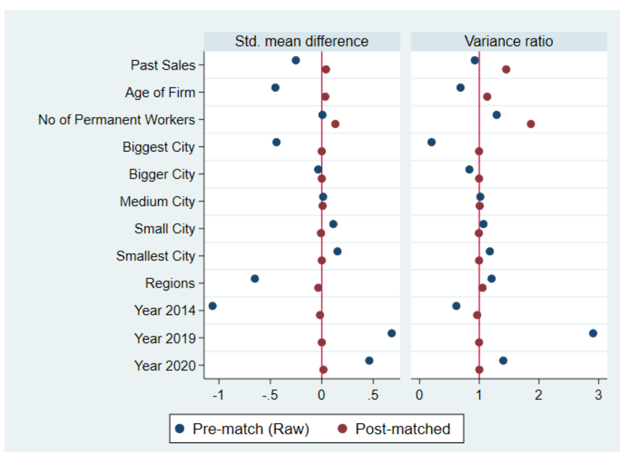

Figure 5.2 This figure shows the standardized differences in the mean values of each covariates as well as the variance ration. The blue dot represents the difference in mean in the pre-match (raw) observation, while the red dot represents the differences in mean post-match using Multivariate-distance nearest-neighbor matching.

Table 5.2 Balancing Statistics

Variable	Treated	Untreated	Std. Diff
Log Past Sales	14.269	14.217	0.031
Age of Firm	22.061	22.318	−0.019E
Permanent Workers	78.689	59.766	0.084
Biggest City (dummy)	0.027	0.027	0
Bigger City (dummy)	0.030	0.030	0
medium City (dummy)	0.246	0.246	−0.00
Small City (dummy)	0.390	0.390	−0.00
Smallest City (dummy)	0.307	0.307	0
Region (dummy)	3.871	4.079	−0.084
Year 2014 (dummy)	3.871	4.079	0
Year 2019 (dummy)	3.871	4.079	0
Year 2020 (dummy)	3.871	4.079	−0.00

Notes: This table provides statistics on treated and untreated observations—firms, post match, using multivariate-distance kernel matching

Table 5.3 Power Outage Effects on Sales in Tunisia

Sales(n = 1,007Introduction)	
(SATE)	(SATET)
Propensity-score matching	
0.055	0.022
(0.45)	(0.19)
Propensity-score kernel matching	
0.044	0.074
(0.27)	(0.50)
Multivariate-distance kernel matching (mahalanobis)	
−0.083	0.046
(0.64)	(0.36)
Multivariate-distance nearest-neighbor matching	
−0.070	0.088
(0.49)	(0.56)

Notes: This table shows OLS estimates for the impact of power outages on firm performance in the full sample of all countries (column1) and each of the four countries (columns 2 through 5). Robust standard errors are clustered at the different regional levels in each country. The measure of outages in Panel A is Outage Hours, while in Panel B, outages are measured using the Outages Dummy. Panel C uses the Yearly Outage measure. Both firm-and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, access to finance, foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

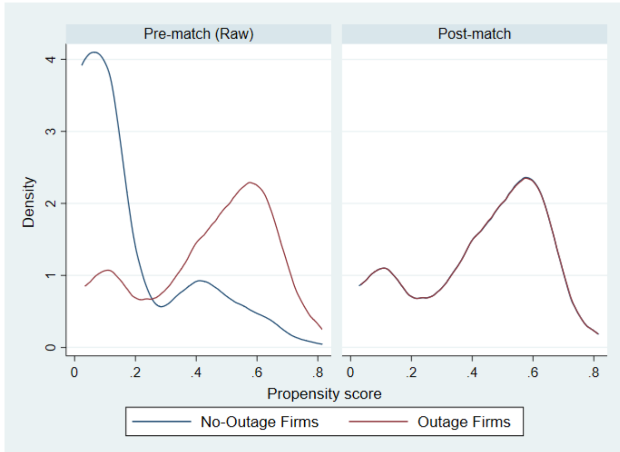

Figure 5.3 This figure shows the propensity scores overlap in the pre-match case (left pane) and post-match (right pane) for treated firms, i.e., firms experiencing outages, and untreated firms, i.e., firms not experiencing outages..

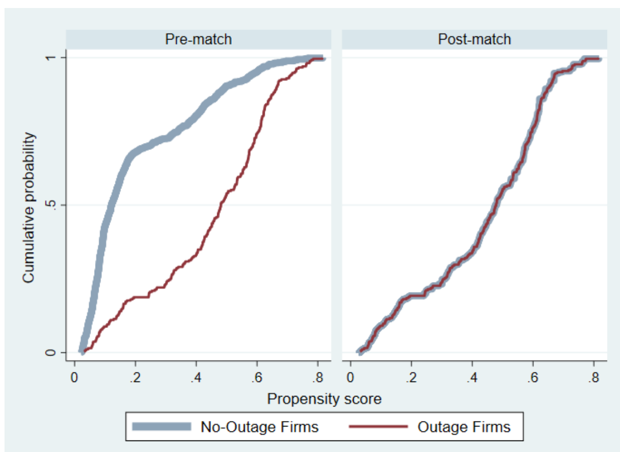

Figure 5.4 This figure shows the cumulative frequency of the propensity scores in the pre-match case (left pane) and post-match (right pane) for treated firms, i.e., firms experiencing outages, and untreated firms, i.e., firms not experiencing outages.

5.4 Conclusion

We use a nationally representative cross-sectional survey from the WBES, covering a total of over 1,000 firms across in Tunisia to investigate the impact of outages on firm performance. OLS estimates of earlier relationship shows a positive association between outages and firm productivity, but such an estimation is likely to be biased as a result of endogeneity. Using matching, we derive, conditional on required assumptions, the effect of outages on firm productivity. Overall, we find that using both SATE and SATET across different matching specifications, power outages have no discernible effect on firm productivity in

Tunisia.

This finding suggest that achieving universal electrification may entail substantial investment in power infrastructure, which strengthens reliability. While outages are not non-existent in Tunisia, they are rather infrequent. Moreover, the fact that only a small subset of firms — 26% — experience outages in a given year suggests that in most parts of the country reliability is rather solid. For many countries that have attained universal electrification, substantial investments have been made in building adequate grid infrastructure especially in urban areas where most commercial activities take place. This finding may be applicable to other high-electrification countries, but further studies with potential to identify the causal effect of outages in these countries are required to make any definitive conclusions.

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APPENDIX A

ADDITIONAL FORMULATION FOR CHAPTER 2

We provide here additional regression tables detailing other results of interest

Table A.1 Power Outage Effects on Valueadded by Country

	All	Morocco	Tunisia	Egypt	Indonesia
	(1)	(2)	(3)	(4)	(5)
			Panel A		
Outage Hours	−0.002	−0.003	0.002	−0.000	−0.005*
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)
Observation	4,848	510	550	2,862	926
R-squared	0.525	0.417	0.563	0.506	0.562
			Panel B		
Outages Dummy (0/1)	0.013	−0.196	−0.007	0.067	−0.015
	(0.054)	(0.166)	(0.198)	(0.053)	(0.195)
Observation	4,848	510	550	2,862	926
R-squared	0.525	0.418	0.563	0.506	0.560
Firm-Level Controls	Y	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y

Notes: This table shows OLS estimates for the impact of power outages on firm performance in each of the full sample of firms in all countries (column 1) and each of the four countries (columns 2 through 5). Robust standard errors are clustered at the different regional levels in each country. The measure of outages in Panel A is Outages hours, while in Panel B, outages are measured using the Outages Dummy. Both firm-and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, foreign ownership, government ownership and city size.

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

Table A.2 Effect of Power Outage on TFP, by Generator Ownership Status and Firm Size

	Generator Ownership		Firm Size		
	Generator	No Generator	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)
			Panel A		
Outage Hours	-0.000	-0.003^{**}	-0.001^{***}	-0.001	-0.002^{**}
	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)
Observation	759	4060	1,926	1,424	1,256
R-squared	0.222	0.035	0.141	0.036	0.125
			Panel B		
Outages Dummy (0/1)	0.033	-0.061	-0.060	-0.034	-0.057
	(0.222)	(0.034)	(0.037)	(0.080)	(0.114)
Observation	759	4060	1,926	1,424	1,256
R-squared	0.587	0.447	0.141	0.036	0.124
Firm-Level Controls	Y	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y

Notes: This table shows OLS estimates for the impact of power outages on firm performance across generator ownership (columns 1 and 2) and firm size categories (columns 3 through 5), for firms in all four countries. Robust standard errors are clustered at the 39 different regional levels in the full sample. The measure of outages in Panel A is Outages Hours, while in Panel B, outages are measured using the Outages Dummy. Both firm-and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, access to finance foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

Table A.3 First Stage OLS

	Outages	
	(Outage Hours)	(Outages Dummy (0/1)
Mean Outage Hours	0.676^{***}	
	(0.092)	
Mean Outages Dummy (0/1)		0.940^{***}
		(0.035)
Manager's Experience	0.041^{***}	-0.000
	(0.014)	(0.000)
No. Permanent Workers	-0.000	-0.000^{*}
	(0.001)	(0.000)
Generator	2.976^{***}	0.885^{***}
	(0.490)	(0.016)
Small Firm	0.433	-2.135^{***}
	(0.459)	(0.077)
Medium Firm	0.428	-1.227^{***}
	(0.483)	(0.813)
Age of Firm	0.001	-0.000
	(0.001)	(0.000)
Foreign Ownership	0.922	0.792
	(0.585)	(0.101)
Government Ownership	-0.021	-0.046
	(1.144)	(0.190)
Bigger City	-0.181^{**}	-0.176
	(0.553)	(0.093)
Big City	-1.123^{***}	-0.819^{***}
	(0.453)	(0.079)
Medium City	-0.456	-0.344^{***}
	(0.526)	(0.087)
Finance Obstacle	-0.456	0.085^{**}
	(0.526)	(0.045)
Observation	8,031	8,031
Montiel-Pflueger F-Stat	53.26	674
R^2	0.014	0.110

Notes: Robust standard errors in parenthesis. In columns 1 and 2, standard errors are clustered at the 39 different regional levels. F-Stat is the IV First Stage F-test of instrument strength. Outage Hours is the total duration of outages a firm experienced in a month. Outages Dummy (0/1) is defined as 1 if a firm experienced an outage in the past year, and 0 otherwise. The instruments are: Mean Outage Hours and Mean Outages Dummy. Small City is omitted in the city-size category, while Large Firm is omitted in the firm-size category.

$p<0.1$; $p<0.05$; $^{**}p<0.01$

Table A.4 Power Outage Effects on Logged Sales by Country — IV Estimates

	Morocco	Tunisia	Egypt	Indonesia
	(1)	(2)	(3)	(4)
		Panel A		
Outage Hours	−0.001	0.002	0.004***	−0.003*
	(0.003)	(0.001)	(0.001)	(0.002)
Montiel-Pflueger F-Stat	46.87	17.79	6.173	33.38
Observation	1,246	1,081	4,522	1,194
R-squared	0.394	0.547	0.448	0.550
		Panel B		
Outages Dummy (0/1)	−0.094	−0.099**	0.068	0.058
	(0.157)	(0.040)	(0.089)	(0.184)
Montiel-Pflueger F-Stat	54.96	19.98	6.14	75.09
Observation	1,246	1,081	4,522	1,182
R-squared	0.400	0.548	0.448	0.550
Firm-Level Controls	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y

Notes: This table shows instrumental variable estimates for the impact of power outages on firm performance in each of the four countries (columns 1 through 4). Robust standard errors are clustered at the different regional levels in each country. The measure of outages in Panel A is Outage Hours, while in Panel B, outages are measured using the Outages Dummy. Both firm-and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, access to finance, foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

Table A.5 Power Outage Effects on Logged Sales by Generator Ownership Category in Each Country — IV Estimates

	Morocco Generator (1)	Tunisia Generator (2)	Egypt Generator (3)	Indonesia Generator (4)
		Panel A		
Ouatges Dummy (0/1)	0.135	−0.266	−0.257	−0.037
	(0.423)	(0.345)	(0.166)	(0.250)
Montiel-Pflueger F-Stat	26.05	14.05	25.08	91.37
Observation	126	110	561	292
R-squared	0.694	0.738	0.621	0.521
	No Generator	No Generator	No Generator	No Generator
		Panel B		
Outages Dummy (0/1)	0.145	-0.113^{**}	0.091	0.009
	(0.180)	(0.054)	(0.121)	(0.165)
Montiel-Pflueger F-Stat	59.35	19.40	5.479	71.95
Observation	1,120	971	3,961	890
R-squared	0.372	0.538	0.405	0.528
Firm-Level Controls	Y	Y	Y	Y
City-Level Controls	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y

Notes: This table shows instrumental variable estimates for the impact of power outages on firm performance in each of the four countries across generator ownership (columns 1 through 4). Robust standard errors are clustered at the different regional levels in each country. Panel A shows the impact of power outages on firm performance for firms owning a generator, using the Outages Dummy measure. Panel B shows the impact of power outages on firm performance for firms without a generator, using the Outages Dummy measure. Both firm- and city-level controls are included in all regressions, including manager's experience, number of permanent workers, size of firm, age of firm, access to finance, foreign ownership, government ownership and city size.
*p<0.1; **p<0.05; ***p<0.01

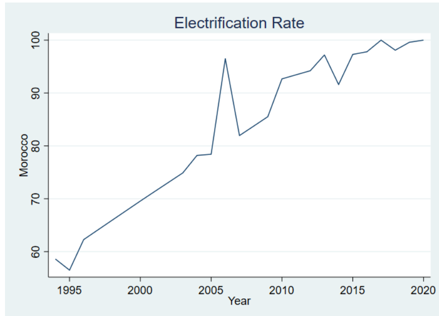

Figure A.1 This figure shows the electrification rate for Morocco, which grew rapidly in the 90s and 2000s, but only reached 100% in 2020.

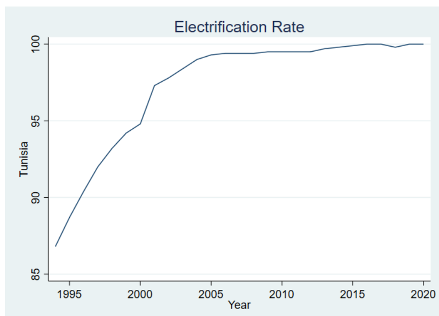

Figure A.2 This figure shows the electrification rate for Tunisia. While electrification rate has peaked since the mid 2000s, it reached 100% in 2016.

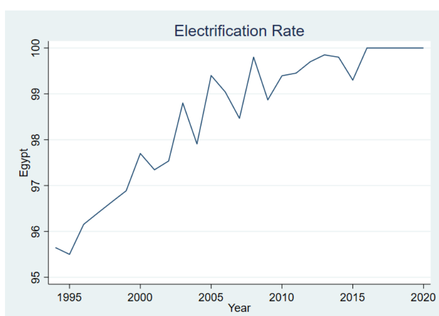

Figure A.3 This figure the electrification rate for Egypt, which has been as high as 95% since 1994, but only reached a 100% in 2016

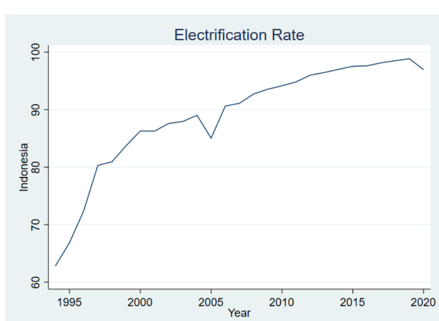

Figure A.4 This figure shows the electrification rate of Indonesia, which grew rapidly in the 90s, and reached a peak of 99%

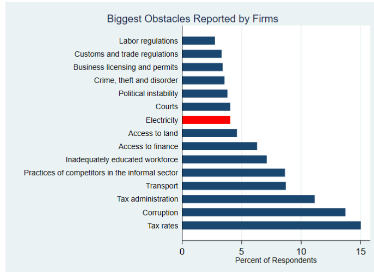

Figure A.5 This figure shows the self-ranking of the biggest obstacles faced by firms in Morocco. Tax rates is ranked as the biggest obstacle while electricity, marked in red, is ranked 9^{th} amid the 15 obstacles identified from firms responses.

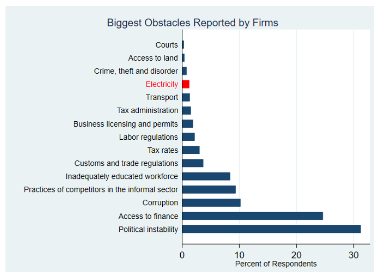

Figure A.6 This figure shows the self-ranking of the biggest obstacles faced by firms in Tunisia. Political instability is ranked as the biggest obstacle while electricity, marked in red, is ranked 12^{th} amid the 15 obstacles identified from firms responses.

Figure A.7 This figure shows the self-ranking of the biggest obstacles faced by firms in Egypt. Political instability is ranked as the biggest obstacle while electricity, marked in red, is ranked 7^{th} amid the 15 obstacles identified from firms responses.

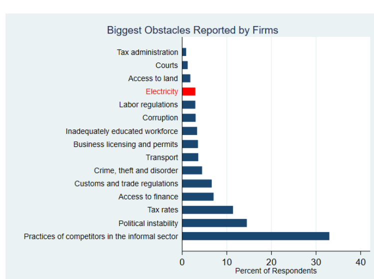

Figure A.8 This figure shows the self-ranking of the biggest obstacles faced by firms in Indonesia. Practices of competitors is ranked as the biggest obstacle while electricity, marked in red, is ranked 12^{th} amid the 15 obstacles identified from firms responses.

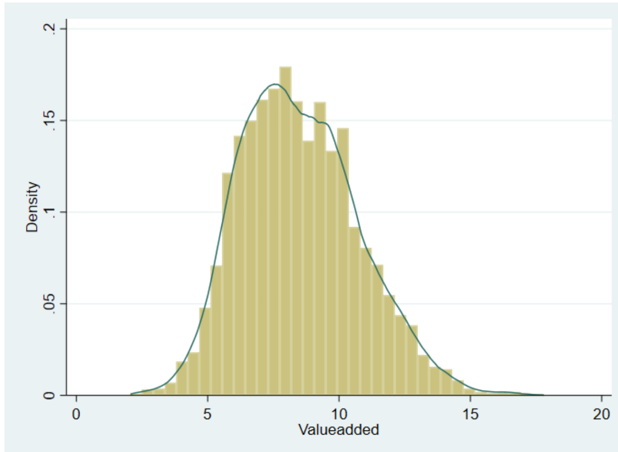

Figure A.9 This figure shows the distribution of valueadded among all firms across the countries we study, which, overall follows a normal distribution.

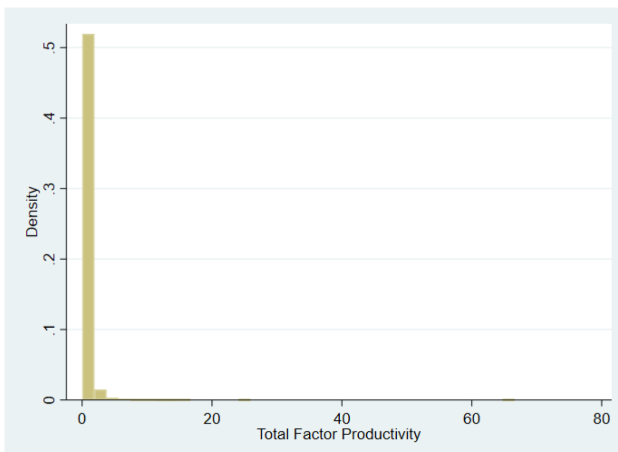

Figure A.10 This figure shows the distribution of total factor productivity among all firms across the countries we study. The distribution appears to be skewed to the left, but for most firm the TFP values fall between 0 and 2, with some outliers above 20 .

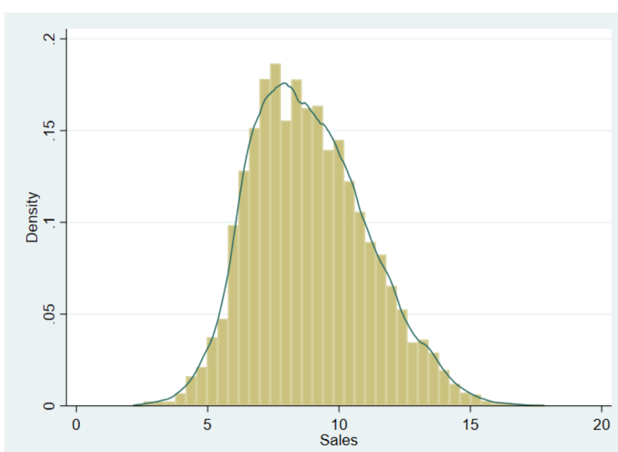

Figure A.11 This figure shows the distribution of sales among all firms across the countries we study, which also follows a normal distribution.

APPENDIX B

DATA AND ADDITIONAL FORMULATION FOR CHAPTER 3

The following notation and description of the constraints are taken directly from Cox et al. [2022] but is included here for convenience. For ease of reference, we repeat the notation introduced in Section 4.

Table B.1 Real-time dispatch model, $(\mathcal{S})$, notation.

Indices and Sets		
t	Time periods in the horizon	
General Time-indexed Parameters		**Units**
Δ_t^{rs}	Estimated fraction of time step t used for receiver start up	-
Δ_t	Duration of period t	h
Δ_t^{e}	Cumulative time elapsed at the end of period t; i.e., $\Delta_t^{\mathrm{e}} = \sum_{t'=1}^{t} \Delta_{t'}$	h
η_t^{amb}	Cycle efficiency ambient temperature adjustment factor in period t	$\mathrm{kW_e/kW_t}$
L_t^{con}	Normalized condenser parasitic loss in period t	-
Q_t^{in}	Available thermal power generated by the CSP receiver in period t	$\mathrm{kW_t}$
W_t^{net}	Maximum net grid transmission in period t	$\mathrm{kW_e}$
$W_t^{\mathrm{u}^+}$	Maximum power production when starting generation in period t	$\mathrm{kW_e/h}$
$W_t^{\mathrm{u}^-}$	Maximum power production in period t when stopping generation in period $t+1$	$\mathrm{kW_e/h}$
γ	Exponential time weighting factor	-
CSP Field and Receiver Parameters		**Units**
D^{rsd}	Time required to complete receiver shutdown	h
D^{rsu}	Minimum time required to complete receiver start-up	h
E^{hs}	Heliostat field start-up or shut down parasitic loss	$\mathrm{kWh_e}$
E^{rsd}	Required energy expended to shut down the receiver	$\mathrm{kWh_t}$
E^{rsu}	Required energy expended to start receiver	$\mathrm{kWh_t}$
L^{r}	Receiver pumping power per unit of power produced	$\mathrm{kW_e/kW_t}$
M	A sufficiently large number	-
Q^{rl}	Minimum operational thermal power delivered by receiver	$\mathrm{kW_t}$
Q^{rsb}	Required thermal power for receiver standby	$\mathrm{kW_t}$
Q^{ru}	Allowable power per period for receiver start-up	$\mathrm{kW_t}$
W^{hco}	Heliostat field communication parasitic draw	$\mathrm{kW_e}$
W^{htf}	Tower piping heat trace full load parasitic draw	$\mathrm{kW_e}$
W^{htp}	Tower piping heat trace part load parasitic draw	$\mathrm{kW_e}$
W^{htr}	Heliostat field tracking parasitic draw	$\mathrm{kW_e}$
Power Cycle Parameters		**Units**
η^{D}	Cycle nominal efficiency	$\mathrm{kW_e/kW_t}$
η^{p}	Slope of linear approximation of power cycle performance curve	$\mathrm{kW_e/kW_t}$
E^{c}	Required energy expended to cold start the power cycle	$\mathrm{kWh_t}$
E^{u}	Energy storage capacity	$\mathrm{kWh_t}$

Table B.1 Continued

E^{w}	Required energy expended to warm start the power cycle	$\mathrm{kWh_t}$
L^{c}	Cycle heat transfer fluid pumping power per unit energy expended	$\mathrm{kW_e/kW_t}$
Q^{b}	Standby thermal power consumption per period	$\mathrm{kW_t}$
Q^{c}	Thermal power input during power cycle start-up	$\mathrm{kW_t}$
Q^{l}	Minimum operational thermal power input to the power cycle	$\mathrm{kW_t}$
Q^{u}	Cycle thermal power capacity	$\mathrm{kW_t}$
$\dot{W}^{\delta+}$	Power cycle ramp-up designed limit	$\mathrm{kW_e/h}$
$\dot{W}^{\delta-}$	Power cycle ramp-down designed limit	$\mathrm{kW_e/h}$
$\dot{W}^{\mathrm{l}}$	Minimum cycle electric power output	$\mathrm{kW_e}$
$\bar{\dot{W}}^{\mathrm{p}}$	Maximum parasitic electrical load	$\mathrm{kW_e}$
$\dot{W}^{\mathrm{u}}$	Power cycle electric power rated capacity	$\mathrm{kW_e}$
W^{b}	Power cycle start-up and standby operation parasitic load	$\mathrm{kW_e}$
W^{c}	Power cycle operating parasitic load	$\mathrm{kW_e}$
Y^{d}	Minimum required power cycle down-time	h
Y^{u}	Minimum required power cycle up-time	h

Initial Condition Parameters		**Units**
Y_0^{d}	Accrued cycle downtime at the start of the horizon	h
Y_0^{u}	Accrued cycle uptime at the start of the horizon	h

Static Continuous Decision Variables		**Units**
$\hat{s}$	Discounted thermal energy in storage at the end of the horizon	$\mathrm{kWh_t}$
s_0	Usable thermal energy	$\mathrm{kWh_t}$

Time-indexed Continuous Decision Variables		**Units**
d_t^{rsd}	Receiver shutdown time inventory in period t	h
d_t^{rsu}	Receiver start-up time inventory in period t	h
f_t^{rsd}	Fraction of period used for receiver shutdown in period t	-
f_t^{rsu}	Fraction of period used for receiver start-up in period t	-
s_t	Usable thermal energy in period t	$\mathrm{kWh_t}$
u_t^{csu}	Power cycle start-up energy inventory in period t	$\mathrm{kWh_t}$
u_t^{rsu}	Receiver start-up energy inventory in period t	$\mathrm{kWh_t}$
u_t^{rsd}	Receiver shutdown energy inventory in period t	$\mathrm{kWh_t}$
$\dot{w}_t$	Power cycle electricity generation in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\delta+}$	Power cycle ramp-up in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\delta-}$	Power cycle ramp-down in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\mathrm{p}}$	Electrical power purchased from the grid in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\mathrm{s}}$	Electrical power sold to the grid in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\mathrm{v}+}$	Power cycle ramp-up beyond designed limit in period t	$\mathrm{kW_e}$
$\dot{w}_t^{\mathrm{v}-}$	Power cycle ramp-down beyond designed limit in period t	$\mathrm{kW_e}$
x_t	Thermal power cycle utilization in period t	$\mathrm{kW_t}$
x_t^{r}	Thermal power delivered by the receiver in period t	$\mathrm{kW_t}$

Time-indexed Binary Decision Variables	
y_t	1 if cycle is generating electric power in period t; 0 otherwise
y_t^{chsp}	1 if cycle hot start-up penalty is incurred in period t (from standby); 0 otherwise
y_t^{csb}	1 if cycle is in standby mode in period t; 0 otherwise
y_t^{csdp}	1 if cycle is shutting down in period t; 0 otherwise
y_t^{csu}	1 if cycle is starting up in period t; 0 otherwise
y_t^{csup}	1 if cycle cold start-up penalty is incurred in period

	t (from off); 0 otherwise
y_t^{cgb}	1 if cycle begins electric power generation in period t; 0 otherwise
y_t^{cge}	1 if cycle stops electric power generation at period t; 0 otherwise
y_t^{r}	1 if receiver is collecting thermal power in period t; 0 otherwise
y_t^{rhsp}	1 if receiver hot start-up penalty is incurred in period t (from standby); 0 otherwise
y_t^{rsb}	1 if receiver is in standby mode in period t; 0 otherwise
y_t^{rsd}	1 if receiver is shutting down in period t; 0 otherwise
y_t^{rsdp}	1 if receiver completes shut down in period t; 0 otherwise
y_t^{rsu}	1 if receiver is starting up in period t; 0 otherwise
y_t^{rsup}	1 if receiver cold start-up penalty is incurred in period t (from off); 0 otherwise

Subject to the following constraints:

Receiver Start-up, See §B.1

$$d_t^{\text{rsu}} \leq d_{t-1}^{\text{rsu}} + \Delta_t f_t^{\text{rsu}} \quad \forall\, t \in \mathcal{T} \tag{B.1a}$$
$$d_t^{\text{rsu}} \leq D^{\text{rsu}} y_t^{\text{rsu}} \quad \forall\, t \in \mathcal{T} \tag{B.1b}$$
$$D^{\text{rsu}} y_t^{r} \leq d_t^{\text{rsu}} + D^{\text{rsu}} \left(y_{t-1}^{\text{r}} + y_{t-1}^{\text{rsb}} \right) \quad \forall\, t \in \mathcal{T} \tag{B.1c}$$
$$u_t^{\text{rsu}} \leq u_{t-1}^{\text{rsu}} + \Delta_t \min \left\{ Q_t^{\text{in}} f_t^{\text{rsu}},\ Q^{\text{ru}} \right\} \quad \forall\, t \in \mathcal{T} \tag{B.1d}$$
$$u_t^{\text{rsu}} \leq E^{\text{rsu}} y_t^{\text{rsu}} \quad \forall\, t \in \mathcal{T} \tag{B.1e}$$
$$E^{\text{rsu}} y_t^{r} \leq u_t^{\text{rsu}} + E^{\text{rsu}} \left(y_{t-1}^{\text{r}} + y_{t-1}^{\text{rsb}} \right) \quad \forall\, t \in \mathcal{T} \tag{B.1f}$$
$$f_t^{\text{rsu}} \leq y_t^{\text{rsu}} \quad \forall\, t \in \mathcal{T} \tag{B.1g}$$
$$f_t^{\text{rsu}} \geq y_t^{\text{rsu}} - y_t^{\text{r}} \quad \forall\, t \in \mathcal{T} \tag{B.1h}$$

Receiver Collection Energy Balance, See §B.2

$$x_t^{\text{r}} \leq Q_t^{\text{in}} \min \left\{ 1 - f_t^{\text{rsu}},\ y_t^{\text{r}},\ 1 - f_t^{\text{rsd}} \right\} \quad \forall\, t \in \mathcal{T} \tag{B.2a}$$
$$x_t^{\text{r}} \geq Q^{\text{rl}} \left(y_t^{\text{r}} - f_t^{\text{rsu}} - f_t^{\text{rsd}} \right) \quad \forall\, t \in \mathcal{T} \tag{B.2b}$$

Receiver Shutdown, See §B.3

$$d_t^{\text{rsd}} \leq d_{t-1}^{\text{rsd}} + \Delta_t f_t^{\text{rsd}} \quad \forall\, t \in \mathcal{T} \tag{B.3a}$$
$$d_t^{\text{rsd}} \leq D^{\text{rsd}} y_t^{\text{rsd}} \quad \forall\, t \in \mathcal{T} \tag{B.3b}$$
$$D^{\text{rsd}} y_t^{\text{rsd}} \geq D^{\text{rsd}} y_{t-1}^{\text{rsd}} - d_{t-1}^{\text{rsd}} \quad \forall\, t \in \mathcal{T} \tag{B.3c}$$
$$u_t^{\text{rsd}} \leq u_{t-1}^{\text{rsd}} + \Delta_t Q_t^{\text{in}} f_t^{\text{rsd}} \quad \forall\, t \in \mathcal{T} \tag{B.3d}$$
$$u_t^{\text{rsd}} \leq E^{\text{rsd}} y_t^{\text{rsd}} \quad \forall\, t \in \mathcal{T} \tag{B.3e}$$
$$E^{\text{rsd}} y_t^{\text{rsd}} \geq E^{\text{rsd}} y_{t-1}^{\text{rsd}} - u_{t-1}^{\text{rsd}} \quad \forall\, t \in \mathcal{T} \tag{B.3f}$$
$$f_t^{\text{rsd}} \leq y_t^{\text{rsd}} \quad \forall\, t \in \mathcal{T} \tag{B.3g}$$
$$f_t^{\text{rsd}} \geq y_t^{\text{rsd}} - y_t^{r} \quad \forall\, t \in \mathcal{T} \tag{B.3h}$$

Receiver Penalties, See §B.4

$$y_t^{\text{rsup}} \geq y_t^{\text{rsu}} - y_{t-1}^{\text{rsu}} \quad \forall\, t \in \mathcal{T} \tag{B.4a}$$
$$y_t^{\text{rhsp}} \geq y_t^{\text{r}} - \left(1 - y_{t-1}^{\text{rsb}}\right) \quad \forall\, t \in \mathcal{T} \tag{B.4b}$$
$$y_t^{\text{rsdp}} \geq y_{t-1}^{\text{rsd}} - y_t^{\text{rsd}} \quad \forall\, t \in \mathcal{T} \tag{B.4c}$$

Logic Associated with Receiver Modes, See §B.5

$$y_t^{\text{rsu}} + y_t^{\text{rsd}} \leq 1 \quad \forall\, t \in \mathcal{T} : Q_t^{\text{in}} > 0 \tag{B.5a}$$
$$y_t^{\text{rsu}} + y_t^{\text{rsd}} \leq 0 \quad \forall\, t \in \mathcal{T} : Q_t^{\text{in}} = 0 \tag{B.5b}$$
$$y_t^{\text{rsu}} + y_{t-1}^{\text{r}} \leq 1 \quad \forall\, t \in \mathcal{T} \tag{B.5c}$$
$$y_t^{\text{rsu}} + y_{t-1}^{\text{rsb}} \leq 1 \quad \forall\, t \in \mathcal{T} \tag{B.5d}$$
$$y_t^{\text{rsu}} + y_t^{\text{rsb}} + y_t^{\text{rsd}} \leq 1 \quad \forall\, t \in \mathcal{T} \tag{B.5e}$$
$$Q^{\text{rl}} y_t^{\text{r}} \leq Q_t^{\text{in}} \quad \forall\, t \in \mathcal{T} \tag{B.5f}$$
$$y_t^{\text{r}} + y_t^{\text{rsb}} \leq 1 \quad \forall\, t \in \mathcal{T} \tag{B.5g}$$
$$y_t^{\text{rsb}} \leq y_{t-1}^{\text{r}} + y_{t-1}^{\text{rsb}} \quad \forall\, t \in \mathcal{T} \tag{B.5h}$$
$$y_t^{\text{rsd}} \geq (y_t^{\text{r}} - y_{t+1}^{\text{r}}) + (y_t^{\text{rsb}} - y_{t+1}^{\text{rsb}}) \quad \forall\, t < |\mathcal{T}| \tag{B.5i}$$
$$y_t^{\text{r}} + y_{t-1}^{\text{rsd}} \leq 1 \quad \forall\, t \in \mathcal{T} \tag{B.5j}$$

Energy Balance, See §B.6

$$\hat{s} = \gamma^{|\mathcal{T}|+1} s_{|\mathcal{T}|} \tag{B.6a}$$
$$s_t = s_{t-1} + \Delta_t \left[x_t^{\text{r}} - \left(Q^{\text{c}} y_t^{\text{csu}} + x_t + Q^{\text{rsb}} y_t^{\text{rsb}}\right)\right] \quad \forall\, t \in \mathcal{T} \tag{B.6b}$$
$$x_{t+1} + Q^b y_{t+1}^{\text{csb}} \leq \frac{s_t}{\Delta_{t+1}^{rs}} - \text{M} \cdot (-3 + y_t^{\text{rsu}} + y_t + y_{t+1} + y_t^{\text{csb}} + y_{t+1}^{\text{csb}}) \quad \forall\, t < |\mathcal{T}| \tag{B.6c}$$

Power Cycle Start-up, See §B.7

$$u_t^{\mathrm{csu}} \leq u_{t-1}^{\mathrm{csu}} + \Delta_t Q^{\mathrm{c}} y_t^{\mathrm{csu}} + (E^{\mathrm{c}} - E^{\mathrm{w}})\, y_{t-1}^{\mathrm{csb}} \quad \forall\, t \in \mathcal{T} \tag{B.7a}$$

$$u_t^{\mathrm{csu}} \geq u_{t-1}^{\mathrm{csu}} + \Delta_t Q^{\mathrm{c}} y_t^{\mathrm{csu}} - E^{\mathrm{c}} y_t^{\mathrm{cgb}} \quad \forall\, t \in \mathcal{T} \tag{B.7b}$$

$$u_t^{\mathrm{csu}} \leq E^{\mathrm{c}} y_t^{\mathrm{csu}} \quad \forall\, t \in \mathcal{T} \tag{B.7c}$$

$$E^{\mathrm{c}} y_t \leq u_t^{\mathrm{csu}} + E^{\mathrm{c}} y_{t-1} \quad \forall\, t \in \mathcal{T} \tag{B.7d}$$

Power Cycle Thermal Input, See §B.8

$$x_t \leq Q^{\mathrm{u}} y_t \quad \forall\, t \in \mathcal{T} \tag{B.8a}$$

$$x_t \geq Q^{\mathrm{l}} y_t \quad \forall\, t \in \mathcal{T} \tag{B.8b}$$

Power Cycle Electric Output, See §B.9

$$\dot{w}_t = \frac{\eta_t^{\mathrm{amb}}}{\eta^{\mathrm{D}}} \left[\eta^{\mathrm{p}} x_t + (\dot{W}^{\mathrm{u}} - \eta^{\mathrm{p}} Q^{\mathrm{u}}) y_t\right] \quad \forall\, t \in \mathcal{T} \tag{B.9a}$$

$$\dot{w}_t \leq \dot{W}^{\mathrm{u}} \frac{\eta_t^{\mathrm{amb}}}{\eta^{\mathrm{D}}} y_t \quad \forall\, t \in \mathcal{T} \tag{B.9b}$$

$$\dot{w}_t \geq \dot{W}^{\mathrm{l}} \frac{\eta_t^{\mathrm{amb}}}{\eta^{\mathrm{D}}} y_t \quad \forall\, t \in \mathcal{T} \tag{B.9c}$$

Power Cycle Ramping, See §B.10

$$\dot{w}_t^{\delta^+} \geq \dot{w}_t - \dot{w}_{t-1} \quad \forall\, t \in \mathcal{T} \tag{B.10a}$$

$$\dot{w}_t^{\delta^-} \geq \dot{w}_{t-1} - \dot{w}_t \quad \forall\, t \in \mathcal{T} \tag{B.10b}$$

$$\dot{w}_t^{\delta^+} - \dot{w}_t^{\mathrm{v}^+} \leq \Delta_t \left[\dot{W}^{\delta^+} + \left(\frac{\eta_t^{\mathrm{amb}}}{\eta^{\mathrm{D}}} W_t^{\mathrm{u}^+} - \dot{W}^{\delta^+}\right) y_t^{\mathrm{cgb}}\right] \quad \forall\, t \in \mathcal{T} \tag{B.10c}$$

$$\dot{w}_t^{\delta^-} - \dot{w}_t^{\mathrm{v}^-} \leq \Delta_t \left[\dot{W}^{\delta^-} + \left(\frac{\eta_t^{\mathrm{amb}}}{\eta^{\mathrm{D}}} W_t^{\mathrm{u}^-} - \dot{W}^{\delta^-}\right) y_t^{\mathrm{cge}}\right] \quad \forall\, t \in \mathcal{T} \tag{B.10d}$$

Power Cycle Minimum Up-time and Down-time, See §B.11

$$y_t^{\mathrm{cgb}} - y_t^{\mathrm{cge}} = y_t - y_{t-1} \quad \forall\, t \in \mathcal{T} \tag{B.11a}$$

$$\sum_{t' \in \mathcal{T}: 0 \leq \Delta_t^{\mathrm{e}} - \Delta_{t'}^{\mathrm{e}} \leq Y^{\mathrm{u}}} y_t^{\mathrm{cgb}} \leq y_t \quad \forall\, t \in \mathcal{T},\ \Delta_t^{\mathrm{e}} > (Y^{\mathrm{u}} - Y_0^{\mathrm{u}}) y_0 \tag{B.11b}$$

$$\sum_{t' \in \mathcal{T}: 0 \leq \Delta_t^{\mathrm{e}} - \Delta_{t'}^{\mathrm{e}} \leq Y^{\mathrm{d}}} y_t^{\mathrm{cge}} \leq 1 - y_t \quad \forall\, t \in \mathcal{T},\ \Delta_t^{\mathrm{e}} > (Y^{\mathrm{d}} - Y_0^{\mathrm{d}})(1 - y_0) \tag{B.11c}$$

$$y_t = y_0 \quad \forall\, t \in \mathcal{T},\ \Delta_t^{\mathrm{e}} \leq \max\left[(Y^{\mathrm{u}} - Y_0^{\mathrm{u}}) y_0, (Y^{\mathrm{d}} - Y_0^{\mathrm{d}})(1 - y_0)\right] \tag{B.11d}$$

Power Cycle Penalties, See §B.12

$$y_t^{\text{csup}} \geq y_t^{\text{csu}} - (y_{t-1}^{\text{csu}} + y_{t-1}^{\text{csb}}) \quad \forall\, t \in \mathcal{T} \tag{B.12a}$$

$$y_t^{\text{chsp}} \geq y_t^{\text{csu}} - (y_{t-1}^{\text{csu}} + 1 - y_{t-1}^{\text{csb}}) \quad \forall\, t \in \mathcal{T} \tag{B.12b}$$

$$y_t^{\text{csdp}} \geq (y_{t-1}^{\text{csu}} + y_{t-1} + y_{t-1}^{\text{csb}}) - (y_t^{\text{csu}} + y_t + y_t^{\text{csb}}) \quad \forall\, t \in \mathcal{T} \tag{B.12c}$$

Logic Associated with Power Cycle Modes, See §B.13

$$y_t^{\text{csu}} + y_t + y_t^{\text{csb}} \leq 1 \quad \forall\, t \in \mathcal{T} \tag{B.13a}$$

$$y_t^{\text{csu}} + y_{t-1} \leq 1 \quad \forall\, t \in \mathcal{T} \tag{B.13b}$$

$$y_t^{\text{csb}} \leq y_{t-1} + y_{t-1}^{\text{csb}} \quad \forall\, t \in \mathcal{T} \tag{B.13c}$$

Power Cycle Operation Restriction, See §B.14

$$y_t + y_t^{\text{csu}} + y_t^{\text{csb}} = 1 \quad \forall\, t \in \mathcal{T} \tag{B.14}$$

Electric Power Sold and Purchased, See §B.15

$$\begin{aligned}\dot{w}_t^{\text{s}} - \dot{w}_t^{\text{p}} = (1 - L_t^{\text{con}})\dot{w}_t - L^{\text{r}}(x_t^{\text{r}} + Q_t^{\text{in}} f_t^{\text{rsu}} - Q^{\text{rl}} y_t^{\text{rsb}}) - \frac{E^{\text{hs}}}{\Delta_t}(y_t^{\text{rsu}} + 2y_t^{\text{rhsp}} + y_t^{\text{rsdp}}) \\ -W^{\text{hco}} - W^{\text{htp}} y_t^{\text{r}} - (W^{\text{htr}} - W^{\text{hco}})(y_t^{\text{rsu}} + y_t^{\text{r}} + y_t^{\text{rsb}}) - W^{\text{htf}}(1 - y_t^{\text{r}}) \\ -L^{\text{c}}(x_t + Q^{\text{c}} y_t^{\text{csu}}) - W^{\text{b}}(y_t^{\text{csu}} + y_t^{\text{csb}}) - W^{\text{c}}(1 - y_t) \quad \forall\, t \in \mathcal{T}\end{aligned} \tag{B.15a}$$

$$\dot{w}_t^{\text{s}} \leq \min\{W_t^{\text{net}} y_t, \dot{w}_t\} \quad \forall\, t \in \mathcal{T} \tag{B.15b}$$

$$\dot{w}_t^{\text{p}} \leq \overline{\dot{W}}^{\text{p}}(1 - y_t) \quad \forall\, t \in \mathcal{T} \tag{B.15c}$$

Additionally, we require:

$$d_t^{\text{rsu}}, d_t^{\text{rsd}}, f_t^{\text{rsu}}, f_t^{\text{rsd}}, p_t^{\text{r}}, p_t^{\text{c}}, p_t^{\text{fw}}, u_t^{\text{csu}}, u_t^{\text{rsu}}, u_t^{\text{rsd}} \geq 0 \quad \forall\, t \in \mathcal{T} \tag{B.16a}$$

$$\dot{w}_t, \dot{w}_t^{\delta^+}, \dot{w}_t^{\delta^-}, \dot{w}_t^{\text{s}}, \dot{w}_t^{\text{p}}, x_t^{\text{r}} \geq 0 \quad \forall\, t \in \mathcal{T} \tag{B.16b}$$

$$0 \leq \dot{w}_t^{\text{v}^+} \leq \dot{W}^{\text{v}^+} \quad \forall\, t \in \mathcal{T} \tag{B.16c}$$

$$0 \leq \dot{w}_t^{\text{v}^-} \leq \dot{W}^{\text{v}^-} \quad \forall\, t \in \mathcal{T} \tag{B.16d}$$

$$0 \leq s_t \leq E^{\text{u}} \quad \forall\, t \in \mathcal{T} \tag{B.16e}$$

$$x_t \geq 0 \quad \forall\, t \in \mathcal{T} \tag{B.16f}$$

$$y_t, y_t^{\text{cge}}, y_t^{\text{chsp}}, y_t^{\text{csb}}, y_t^{\text{csdp}}, y_t^{\text{csu}}, y_t^{\text{csup}}, y_t^{\text{cgb}} \in \{0, 1\} \quad \forall\, t \in \mathcal{T} \tag{B.16g}$$

$$y_t^{r}, y_t^{\text{rhsp}}, y_t^{\text{rsb}}, y_t^{\text{rsd}}, y_t^{\text{rsdp}}, y_t^{\text{rsu}}, y_t^{\text{rsup}} \in \{0, 1\} \quad \forall\, t \in \mathcal{T} \tag{B.16h}$$

We maximize plant revenue given as profit from the sale of electricity to the utility grid less the cost of purchases from the grid and estimates of operations and maintenance due to dispatch decisions throughout the time horizon in question as seen in the objective function, given in (3.1), omitting the spinning reserves term.

B.1 Receiver Start-up

Constraints (B.1a)-(B.1c) require a start-up time "inventory" be fulfilled, in addition to the start-up energy "inventory" in constraints (B.1d)-(B.1f). The D^{rsu} parameter defining the time to complete receiver start-up could be set by a plant operator depending on how well the receiver was last drained. We employ a common continuous decision variable in both requirements which represents the fraction of the current period used for the start-up process. This variable is controlled by the start-up and operation binary variables in constraints (B.1g)-(B.1h). The remaining fraction of the last period of start-up may be used for collection.

B.2 Receiver Collection Energy Balance

The parameter Q_t^{in} provides an upper bound on the amount of thermal power the receiver can collect in each period, which is reduced by the fraction of the current period used for receiver start-up or shutdown in constraint (B.2a). The receiver operating binary forces the power collected to zero for periods in which the receiver is not operating. Receiver power collection must be greater than its non-zero lower bound Q^{rl} during periods in which it is operating, but we relax this lower bound by the fraction of the period used for receiver start-up or shutdown in constraint (B.2b).

B.3 Receiver Shutdown

Similar to the receiver start-up process, a receiver shutdown process consists of draining the receiver tubing while thermal energy is applied to the receiver by the heliostat field. We use an analogous formulation of this process having both a time "inventory" in constraints (B.3a)-(B.3c) and an energy "inventory" in constraints (B.3d)-(B.3f). We employ a common continuous decision variable in both requirements which represents the fraction of the current period used for the shutdown process. This variable is controlled by the shutdown and operation binary variables in constraints (B.3g)-(B.3h). The remaining fraction of the first period of shutdown may be used for collection.

B.4 Receiver Penalties

Constraints (B.4a)-(B.4c) enforce objective penalties for receiver start-up, hot start-up, and shutdown, respectively. These penalties are used to impose estimates of maintenance costs due to these operating decisions in the objective.

B.5 Receiver Logic

Constraints (B.5a) and (B.5b) require that there be non-zero solar resource for the receiver to be in one of the start-up or shutdown modes. Start-up is precluded if the receiver was in the collection or standby modes in the previous period by constraints (B.5c) and (B.5d). Further, constraint (B.5e) applies a packing constraint to preclude the receiver being in more than one of the start-up, standby, or shutdown modes in the same time period. Constraint (B.5f) enforces a lower bound on the available solar resource during periods in which the receiver is in collection mode. Constraint (B.5g) prevents the receiver from simultaneously being in collection and standby modes, though we do allow the receiver to be in start-up or shutdown modes for a portion of a period (relaxed for start-up in constraint (B.1h) or shutdown in constraint (B.3h)) and in collection mode for the remainder of the period. Constraint (B.5i) requires the receiver to enter the shutdown mode when exiting the collection or standby modes, and constraint (B.5j) forces the receiver out of collection mode after entering shutdown. These constraints allow the receiver to be collecting and in shutdown for a single period and solely in the shutdown mode in subsequent periods, until the shutdown process has completed.

B.6 Energy Balance

Constraint (B.6b) accounts for contributions to the usable thermal energy in storage collected at the receiver, and reductions from usable thermal energy to complete power cycle start-up, produce electricity, or maintain the receiver in standby. Constraint (B.6b) is sufficient to model thermal energy storage during periods using the linear formulation. We do not separate hot and cold storage in this representation, nor is there a representation of the temperature of the heat transfer fluid (HTF) holding this energy. The efficiency at which this thermal energy is converted to electrical energy is dependent on this temperature, is commonly referred to as the "quality" of the energy, and is a primary consideration in plant operations.

B.7 Power Cycle Start-up

Power cycle start-up enforced by constraints (B.7a)-(B.7d) is analogous to receiver start-up, but we only insist on an energy "inventory" requirement to complete power cycle start-up, because this process is not dependent on the variable output of the heliostat field. Constraint (B.7a) includes an energy incentive if the power cycle was in the standby mode prior to start-up. This incentive allows the power cycle to start up more quickly for cases in which it was previously in standby mode, and is formulated similarly to warm-start constraints in the unit commitment literature [Simoglou et al., 2010]. Constraint (B.7b) enforces a lower bound on the cycle start-up energy "inventory" to prevent prolonging power cycle start-up, which could allow the model to ferry HTF from the hot tank back to the cold tank, and is not an operation mode we consider.

B.8 Power Cycle Thermal Input

Constraints (B.8a) and (B.8b) control the thermal input to the power cycle in periods using the linear formulation, and reduce the upper and lower bounds, respectively, on thermal input to the power cycle based on a linear function of the bulk temperature of the hot storage tank. These reductions reflect bounds on the mass flow rate input to the power cycle (physically imposed by system pumping limits), and assume a constant hot storage tank bulk temperature over all periods using the linear formulation.

B.9 Power Cycle Electric Output

Constraints (B.9a), (B.9b), and (B.9c) are sufficient to control the production of electric power in periods using the linear formulation. Constraint (B.9a) enforces a linear model of power cycle efficiency with respect to the level of thermal input. Constraints (B.9b) and (B.9c) enforce non-zero upper and lower bounds, respectively, on power cycle output during periods in which the power cycle is in generation mode.

B.10 Power Cycle Ramping

Constraints (B.10a) and (B.10b) enforce the definition of the positive and negative electric output ramping variables. Constraints (B.10c) and (B.10d) enforce upper bounds on the power cycle output ramping variables, which are reduced if production is started or ended in the current period. These bounds are elasticized by the ramping violation variables $\dot{w}_t^{\mathrm{v}^-}$ and $\dot{w}_t^{\mathrm{v}^+}$, which have greater objective penalties than the ramping variables.

B.11 Power Cycle Up and Down Times

We adopt a formulation of minimum up-time and down-time requirements on the power cycle developed in the unit commitment literature [Morales-España et al., 2013, Garver, 1962], to enforce minimum duration for the power cycle to be in (or out of) generation mode. Constraint (B.11a) relates the operating binary to the start and end generation binaries. Constraint (B.11b) enforces minimum up-time by forcing the operating binary to 1 until the sliding window defined by the minimum up-time parameter no longer contains a non-zero value of the begin-production binary variable. Constraint (B.11c) similarly enforces the minimum down-time. Constraint (B.11d) serves as an initial condition for either minimum up-time or down-time depending on the value of the operating binary initial condition y_0. This formulation allows the integrality of the indicator binary variable y_t^{cgb} and y_t^{cge} to be relaxed to be continuous between 0 and 1.

B.12 Power Cycle Penalties

Constraints (B.12a)-(B.12c) enforce objective penalties for power cycle start-up, hot start-up, and shut down, respectively. These penalty variables are used to enforce estimated maintenance costs in the objective.

B.13 Logic Associated with Power Cycle Modes

Constraints (B.13a)-(B.13c) enforce binary logic on power cycle operations. Constraint (B.13a) requires that the power cycle be in at most one of its operating modes in a single time period. Constraint (B.13b) precludes the cycle being in start-up mode in periods after it was in production mode. Constraint (B.13c) requires that the power cycle be in either production or standby modes in the previous period if it is in standby mode in the current period.

B.14 Power Cycle Operation Restriction

Due to our problem horizon, we expect the power cycle to complete only one or two start-ups, returning to standby operation when not generating power. However, solutions to the dispatch model ($\mathcal{R}$) typically include shutting down the power cycle at the end of the horizon. This contributes to an end-of-horizon effect, because the time required to restart the power cycle after a completed shutdown would be detrimental to plant revenue on the subsequent day. We mitigate this effect by requiring the power cycle to operate either in start-up, generation, or standby modes for the entire problem horizon (see constraint (B.14)). The decision to shut down the power cycle could be made by this formulation, but requires an appropriate end-of-horizon incentive.

B.15 Grid Operations

Constraint (B.15a) accounts for electric production and plant parasitic loads. The electric output of the power cycle is reduced by a multiplicative factor representing the power required to operate the steam condenser portion of the power cycle, which is dependent on ambient temperature and varies with respect to the current time period. Other parasitic loads are then subtracted from this net electric output, including HTF and feedwater pumping power, heliostat and heat trace parasitic load, and the power needed to run auxiliary boilers and heat tracing according to the current power cycle operating state. Constraints (B.15b) and (B.15c) provide upper bounds for the electric power sold and purchased, respectively. Changes to the heliostat tracking fraction incur the electric energy load E^{hs}, which is time-averaged over the duration of the current time period. We include linear models of pumping parasitic loads, which depend on receiver and power cycle thermal input, using the linear formulation. Periods using the nonlinear formulation include piece-wise linear models of pumping parasitic loads, and depend on the mass flow rate input to the receiver or power cycle fit to plant operational data.