Measuring Downstream Supply Chain Losses Due to Power Disturbances

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Abstract

Power outages in the U.S. affect many firms' economic activity and are likely to result in downstream supply chain disruptions. This paper examines the impact of power disturbances in the supply chain for four industries: manufacturing, durable goods manufacturing, nondurable goods manufacturing, and total private industry. This indirect impact includes the losses at downstream firms that might not receive supplies on time due to disturbances at their suppliers' facilities. This is measured using observations of value added before and after power disturbances rather than the more common method of modeling an economy. This paper tests four hypotheses related to the effect of power disturbances with all four of them being supported by the model results. Further, using simulation we estimate the indirect costs of power disturbances. The results suggest that power disturbances have a statistically significant effect on gross domestic product (i.e., value added), particularly in manufacturing where power disturbances in the supply chain had a statistically significant effect. While this industry represents 12.8 % of private industry value added, it experiences 36.8 % of the supply chain losses due to power disturbances, as suggested by the results of the simulation. Power disturbances in the supply chain affected all four industries with nondurable goods being affected the most. This creates a significant disconnect between the stakeholder that invests in reliability in the power grid and the stakeholders that experience the bulk of losses.

1. Introduction

According to a PwC study, 75 % of firms in the U.S. experience a major supply chain disruption annually (PwC 2015). Hurricanes, wildfires, and other major events can cause severe disruption. For instance, Mukherjee et al. (2018) developed a model to assess power-outage risk to severe weather events and found that the electricity sector is most vulnerable to prolonged outages due to wind events (such as hurricanes, tornadoes, winter storms, wind-storms). Nevertheless, power outages that occur more frequently as everyday events unrelated to natural hazards can also cause significant disruption. These outages can result in losses at businesses and may reduce competitiveness. In addition to direct impacts, there are also indirect impacts. A firm that loses power may not be able to deliver supplies on time to other firms.

Metrics for examining outages suggest that the U.S. has a wide range of performance. The system average interruption duration index (SAIDI), which measures the average amount of time per year that power supply to a customer is interrupted at the utility level (Campbell 2012), ranged between 0.7 minutes and 4150.0 minutes for U.S. utilities in 2019 (Energy Information Administration 2020a).[1] The system average interruption frequency index (SAIFI), which measures the average number of times per year that the supply to a customer is interrupted (Campbell 2012), ranged between 0.01 and 16.45.[2] These ranges are the result of a number of factors, including the type of energy infrastructure, investment in infrastructure, and the risks faced by a region (e.g., wind, tornados, and floods). Nonetheless, these regions need to consider the costs and benefits of reliable energy infrastructure.

[1] When excluding major event days, it ranged between 0.7 and 1239.3.
[2] When excluding major event days, it ranged between 0.01 and 12.39.

As discussed by the Energy Information Administration (2020b), U.S. electricity is delivered through a complex system where supply is delicately balanced with demand. If this balance is disturbed, widespread blackouts can occur. Energy is largely produced at power plants. Then, it is stepped up to high voltage for long distance transmission using transformers and then stepped back down for local transmission. Interconnections of the power grid across the U.S. and Canada maintain reliability by providing multiple routes for energy to flow to consumers. In the lower 48 states, there are three main interconnections that operate independently from each other: Eastern Interconnection, Western Interconnection, and the Electric Reliability Council of Texas. There are only limited transfers between the three interconnections. Some of the lines in the transmission process have reached the end of their useful life and need replacement, making them vulnerable during hazardous events. According to Edison International, the most common causes of widespread outages are wind, heat, ice, and snow (Edison International 2016).

It is estimated that 90 % of outages in the U.S. are due to a disruption in the local power distribution system (Campbell 2012). Table 1 uses data from a study by Hines et al. (2008), which provides some insight into the causes of outages. Some cause categories in Table 1 are more frequent, but result in less disruption (i.e., time to restoration, lost electricity, or affected customers). Two risk metrics show that wind/rain are a major risk as well as equipment failures and hurricanes/tropical storms, depending on the metric. Some causes result in more electricity losses while others affect more customers. The impact of outages, however, is not well understood, particularly the downstream impact.

A survey of 251 commercial and industrial companies (S&C Electric Company 2018) reveals that 21 % experienced a power outage once a month and 49 % had an outage once a year. Approximately 26 % reported outages lasting on average more than an hour. Of the respondents, 52 % indicated that they were not fully satisfied with their power reliability and for 18 % of the respondents, their worst power loss cost more than $100 000. These results suggest that there are potentially significant impacts from power outages in the U.S. with additional downstream impacts.

The losses that result from power disturbances can be classified by the point in the supply chain where the losses occur and the relative time period in which the losses occur. In terms of the supply chain point, losses are incurred by those that experience the power disturbance, by those that are supplying the firms that experienced the disturbance (upstream), and by those that are being supplied by the firms that experienced the disturbance (downstream). In terms of the time period in which losses are incurred, there are short-term losses that occur immediately following an event and then there are long-term losses that result from disturbances. This paper examines the short-term downstream impacts from power disturbances. This impact includes the losses at downstream firms that might not receive supplies on time due to outages at their suppliers' facilities. Our analysis examines manufacturing, durable goods, nondurable goods, and total private GDP in the U.S., using regression analysis, where losses are measured in terms of value added.

The paper is organized as follows. Section 2 reviews the literature on estimating impacts of power outages. Section 3 presents the data used in the analysis followed by Section 4, the methods section, which describes the models and variables. Section 5 presents estimation results. Summary and conclusions are provided in Section 6 and Sections 7.

2. Literature

Direct Losses/VoLL. The standard approach to estimating direct power-related losses is to estimate the Value of Lost Load (VoLL). The VoLL is the value of one unit of electricity, which can be interpreted as a firm's value added due that is lost due to a power outage (Castro et al. 2016). There are three main approaches to estimating VoLL in the literature: stated preference, the production-function approach, and case studies (Linares and Rey 2013). The approaches are not mutually exclusive; for instance, the case study approach is relevant when there is a history of power outages available and is therefore often combined with the other two approaches.

The stated-preference approach relies on collecting surveys to estimate VoLL. Serra and Fierro (1997) conduct a survey of businesses in Chile, across each of the Standard International Industrial Classification (SIIC) classes. They find that a 10 % restriction of electricity per month results in average net outage costs between $3.2 and $7.7 per kWh. Diboma and Tatieste (2013) conduct a survey of firms in Cameroon to estimate the costs of power outages and find that average costs between $3.62 and $5.42 per kWh for a one-hour outage and between $1.96 and $2.46 per kWh for a 4-hour outage. Oseni and Pollitt (2015) estimate losses from power outages for small businesses in Sub-Saharan Africa, comparing firms that have backup generation to firms that do not in the World Bank Enterprise Survey. Firms with backup generation experience power-related losses ranging from about $2 to $24 (USD) per kWh, while firms that do not have backup generation experience losses ranging from about $1.50 to $32 per kWh. Woo et al. (2014) use a contingent valuation survey of households in Hong Kong to estimate preferences for power reliability. They find that households are not willing to accept a lower electricity bill rate for reduced power reliability, with the average cost of a 1 kWh of power outage estimated at $45. It is important to note that studies of other countries can provide insight into the losses due to power disturbances; however, there are differences in the economies and infrastructure for each country that may significantly affect losses. The extent to which these studies extend to the U.S. and other countries is unclear. Finally, Kim and Cho (2017) collect survey data from firms in South Korea to estimate the cost of unannounced and preannounced power outages. They find that preannouncing outages reduces costs to firms, and this reduction varies by sector. The paper is unique in incorporating indirect costs such as overtime to make up for lost production; damage to raw materials, finished product, and equipment; cleanup costs; and other damages experienced due to an outage, in addition to direct costs from production losses.

The production function approach is a proxy method that estimates VoLL indirectly as the ratio of an economic measure, such as value added, to electricity consumption (typically one kilowatt hour, or kWh). Linares and Rey (2013) use a production function approach to estimate the cost of electricity outages to households and industry in Spain. They find that one kWh of power not supplied in 2008 costs Spain 6 Euros across all sectors, with the cost to manufacturing of about 1.5 Euros, the cost to households and transportation about 8 Euros, and the cost to construction about 33 Euros. Similarly, Castro et al. (2016) use a production function approach to estimate the VoLL for Portugal in the context of deregulation and renewable energy. They estimate an average VoLL of 5.12 Euro/kWh, with construction and public works having the highest VoLL at 15.52 Euro/kWh. Wolf and Wenzel (2016) estimate the impacts of power outages for firms and households at the county-level in Germany. For manufacturing, they estimate the VoLL to be between 0.48 Euro/kWh and 12.49 Euro/kWh, with the highest VoLLs found in counties with energy-intensive production. Finally, Zachariadis and Poullikas (2012) utilized a large-scale power disruption in Cyprus during the summer of 2011 to estimate the impact of emergency government measures to reduce losses. Using an approach that combines a case study with the production-function method, they estimate annual losses from the power disruption across households and industry to be between 200 million Euros, with emergency measures (e.g., consumers reducing energy consumption and power companies purchasing generators), and 400 million Euros, without emergency measures.

Economic Losses/Productivity. In contrast to estimating direct losses such as VoLL, there are no standard approaches to estimating the economic impact of power outages. Shuai et al. (2018) review the literature on the economic losses associated with power outages, including typical methodological approaches. The authors find that there is little research on estimating indirect economic losses and identify three distinct views on defining indirect impacts: (1) the "other" costs incurred due to an outage, such as cleanup costs and using generators (as in Kim and Cho (2017); (2) psychological impacts and other impacts that are difficult to monetize; and (3) the impacts due to insufficient supply of commodities on consumption and industrial production. Our paper fills the third gap.

Many studies on economic losses due to power outages rely on firm level survey data. For instance, Moyo (2013) estimates the impact of the quality of power infrastructure on firm productivity. Using World Bank Enterprise Survey (WBES) data for firms in Africa, the author finds that the number of hours per day without power and output lost due to outages have a negative impact on productivity, with firms that own generators minimizing the negative impacts in Uganda, Tanzania, and Mauritius. Adbasi (2018) uses the WBES to study productivity impacts on firms in Ethiopia and finds that power outages increase firm costs by 15 %. Fisher-Vanden et al. (2015) estimate the impacts of electricity shortages on firm productivity in China. Using a panel of firms from 1999-2004, they find that firms were able to offset productivity losses by substituting materials for energy and engaging in costly outsourcing, with production costs increasing by 8 %. Grainger and Zhang (2019) conduct a survey of manufacturers in Pakistan and estimate productivity losses due to power outages. They find that a one-hour outage decreases annual value added by 20 % and decreases annual revenue by 10 %.

Cole et al. (2018) caution that power outages may be endogenous, that is, the factors that affect power outages may also affect productivity. One possibility is that government investment in infrastructure may be motivated by government support of certain firms or industries. For instance, a state or local government might improve infrastructure for a business to keep jobs local. Another factor may be that firm location may be driven by power reliability. Finally, self-reported power outages may be biased by a firm's productivity. Alam (2013) studies the impacts of power outages on steel and rice mills in India. Using satellite data as an objective measure of power outages, the author finds that firms adapt and reoptimize to deal with shortages. Moreover, only steel mills experience a decrease in profits even though both industries adapt to outages by using less publicly provided power. Alcott et al. (2016) estimate the impact of power outages on manufacturing firms in India. Using shifts in demand for hydroelectric power to instrument for shortages, they find an average reduction in firm revenue between 5 % and 10 %, while productivity losses are mitigated by the ability to store inputs during an outage. Cole et al. (2018) use data from the WBES to analyze the impact of power outages on firm sales, profits, and productivity in Sub-Saharan Africa. Using variation in hydro-power consumption due to local climate, they find that the reduction in sales is much larger when accounting for endogeneity (between 83 % and 117 % with the instrument, versus between 3.8 % and 12.4 % without). Finally, Abeberese et al. (2019) study the impact of power outages on manufacturing productivity in Ghana. Using a government power-rationing program as a source of exogenous variation, they find that such power outages result in reduced productivity, and that generators are not enough to mitigate the negative impacts of outages.

Other methods include hybrid approaches as well as computational modeling. Coll-Mayor et al. (2012) present a general methodology that builds on the production-function approach for estimating VoLL to estimate the economic losses from power outages. The method estimates economic losses as a function of VoLL, actual power lost in a disruption, and hours of production downtime. The methodology is illustrated on five regions in Spain, with losses ranging from about $200 000 Euros to nearly $60m Euros, depending on the region and zone (e.g., urban or rural). Larsen et al. (2018) present a very different approach to project the long-run costs of power interruptions in a model that incorporates regional models of power-system reliability and severe weather. They find total costs to residential and commercial customers in the United States between $1.5 and $3.5 trillion by the year 2050, depending on the level of undergrounding and operations and maintenance. Finally, Fried and Lagakos (2020) construct a dynamic general equilibrium model that includes electricity as an input, as well as rationing and self-production via generators, both of which are common in the developing world. They find that while the short-run impacts on productivity from reducing outages are small, the long-run impacts are much larger. Other studies utilizing general equilibrium models include Rose et al. (2005), who examines the effects of four rolling blackouts in Los Angeles County; Rose et al. (2007), who examine power loss in Los Angeles due to terrorist attacks; Guha (2005), who examines the effect of power outages in Tennessee due to natural hazards; Wing and Rose (2018), who examine a two-week power outage in the California bay area. Rose et al (1997) also examine a hypothetical power outage in Shelby County, TN using input-output analysis, another method for measuring direct and indirect effects. It is worth mentioning that while some of these studies consider indirect effects in a computational model, they do not explicitly account for the short-term downstream effects of a firm experiencing a power outage. There are different types of indirect effects with downstream supply chain effects being one of the indirect effects that are not well understood.

GDP. There is also literature that investigates the effect of power outages on the macroeconomy. Andersen and Dalgaard (2013) estimate the effect of power outages on economic growth in Sub-Saharan Africa, using a combination of GDP and satellite imagery data. Das and McFarlane (2019) study the dynamics of electric power losses and GDP in Jamaica. They find that electric power losses have a negative impact on GDP that persists in the long run. There is also a related literature studying the relationship between electricity consumption and GDP (for instance, Ho and Siu 2007; Huang et al. 2008; Fallahi 2011).

WTP. Another strand of literature attempts to estimate the willingness-to-pay (WTP) for power reliability, or willingness-to-accept (WTA) power disruptions. Carlsson et al. (2020) estimate small business willingness-to-pay for reductions in power outages. Using a stated preference survey in Ethiopia, they find small businesses are willing to pay the equivalent of a 16 % tariff increase for a reduction of one power outage. Ghosh et al. (2017) conduct a contingent valuation analysis of small manufacturers in India and find that firms are willing to pay 20 % more in electricity bills, on average, to avoid power outages. Niroomand and Jenkins (2020) conduct a survey of households and firms in Nepal to estimate willingness to pay for a 50 % reduction in outages and a total reduction in outages. For businesses, they find a median WTP of 20 % of their current bill for a 50 % reduction and 62 % of their current bill for a total reduction.

There are also many studies focused on estimating households' WTP to avoid power outages. For example, Ozbafli and Jenkins (2016) estimate household willingness-to-pay for reductions in power outages in North Cyprus. Using a choice experiment approach, they estimate that households are willing to pay 3.6 % more per month in the summer and 13.9 % more per month in the winter to avoid power outages. Carlsson et al. (2011) conduct a contingent-valuation survey of Swedish households and find that experience with outages actually decreases WTP. See also WTP studies by Pepermans (2011) on Flemish households and Abrate et al. (2016) on Italian households.

Literature Summary: Table 2 categorizes the literature and methods discussed above by the point in the supply chain where the measured losses occurred and the relative time period in which the measured losses occurred. Although the delineation between short-term and long-term losses is vague, short-term losses are generally those that occur during the days or weeks in which a power disturbance occurs while long-term losses are those that occur in the months or years following a disturbance. Upstream losses are those experienced by the suppliers to establishments that experienced a power outage (e.g., losses due to a decrease in orders) while downstream losses are those that experience loss as a result of their suppliers experiencing a power outage (e.g., shortage of supplies). Direct losses are those that occur at the establishment that experienced the power outage. Note that a great deal of the literature falls into the category of direct short-term losses. That is, the literature has significant coverage of the losses that occur at the establishments that experience a power disturbance and at the time of the disturbance. There are also a number of papers discussing upstream losses and long-term losses; however, we did not identify literature examining the downstream short-term losses. That is, the immediate shortages or delays that result from having suppliers that experience a power disturbance. This paper falls into that category. It is important to note that long-term losses are often measured using computable general equilibria models, which determine a new economic equilibrium given economic disruptions. These theoretical equilibriums take time to occur, making them long term effects. Generally, these models do not estimate the losses that might occur when supplies fail to arrive on time immediately following a power disturbance. The next section discusses the data used in this analysis.

3. Data

This analysis uses quarterly data on U.S. value added and "electric disturbance events" by state. The value-added data is from the Bureau of Economic Analysis and includes data on U.S. manufacturing, durable goods, nondurable goods, and total private industry in chained 2012 dollars (Bureau of Economic Analysis 2020). Data on the duration of "electric disturbance events" is provided by the Department of Energy (Department of Energy 2020). It includes the start and end time of the event, which we used to calculate the duration in hours. Each disturbance event indicates the location of the event, which can be a city, county, state, or other geographic entity. For this analysis, we identified all the states involved affected by the disturbance. A summary of the data is found in Table 3. A supply chain variable, described below, is also summarized. The precision in the electric disturbance data is unclear. For instance, the geography for affected areas is often vague and the customers affected often appears to be rounded up/down. Issues of this nature will reduce the statistical significance in the analysis, making our estimate a conservative estimate.

For measures of the domestic flow of goods, data from the Freight Analysis Framework (FAF) was used and accessed through the US Department of Transportation (2018). FAF data provides shipments of goods by origin and destination for each of the 50 states covering the entire US from 2002 through

2016. For years 2002 through 2006, the FAF 2002 data was used. For years 2007 through 2012, the 2007 data was used. After 2012, annual data is available. For this paper, the dollar value of a selection of goods was used. These industries were selected to represent intermediate goods that might have low levels of substitutability and include nonmetal mineral products, base metals, articles-base metal, machinery, electronics, motorized vehicles, transport equipment, and precision instruments. The last two datasets used are from the Annual Survey of State and Local Finances (U.S. Census 2020) and private nonresidential construction (U.S. Census 2021).

4. Methods

This analysis tests four hypotheses using four models (see Table 4) to examine the effect of power disturbances in the supply chain on value added locally. Note that the terms "local" and "supply chain" are used to distinguish between the geographic location of the power disturbances (local) and the geography of the supply chain locations. There are four variations on the two hypotheses with the difference being the industry being examined: manufacturing, durable goods, nondurable goods, and total private industry (see Table 4 for details). The study period for the analysis is 2005 through the second quarter of 2020.

There are a limited number of studies on the impact of power disruptions on downstream value added, but there are studies examining the effects of research/development and productivity (Ugur et al., 2016). Two approaches are commonly used for such an analysis: the primal approach (production function) and the dual approach (cost function) with the primal approach being more predominant (Ugur et al., 2016). This paper adopts the primal approach and uses a Cobb-Douglas production function. These models tend to use real output as the dependent variable with research and development capital, capital stock, labor (number of employees or hours worked), and technological progress as independent variables:

$$Q = Ae^{\lambda} C^{\beta_{x1}} L^{\beta_{x2}} K^{\beta_{x3}} \mathcal{E}^{\beta_{x4}}$$

where

Q = Real output

C = Real capital stock

K = Real research and development capital

L = Labor (number of employees or labor hours worked)

Ae^{λ} = is technological progress with a rate of disembodied technological change λ

β_{xn} = Estimated parameters

In this instance, we use lagged dependent variables to control for capital, labor, and other factors. It also controls for factors that might happen to correlate with power outages and reduces the likelihood that we are identifying spurious or meaningless correlations. Cobb-Douglas production functions have also been used to examine natural hazard impacts (Mohan et al., 2019), which is closely related to power disruptions; however, there are also non-hazard causes for power disturbances.

Real value added, a measure of real output, is the dependent variable with the model including lagged dependent variables. There are also three indicator variables that indicate the second, third, and fourth quarters of the year. The total duration in hours for all power disturbances is included as an independent variable.[3] This includes any incident that indicates that that state or a geographic area within that state occurred. A supply chain variable, representing tier 1 suppliers for a state, is included which is the sum of the duration of disturbances within the top 10 supply chain states weighted by the annual dollar value of shipments originating in each state. A common idiom is that 20 % of the cause represents 80 % of the problem. For this reason, the top 10 states were selected as this represents the top 20 % of supply chain entities. Recall that the FAF data, which is used to identify the top supply chain entities and weight supply chain effects, is not available annually for all years. The effect of this should be minimal. The proportions that are calculated using the FAF data (discussed below) change slowly for a particular location. Thus, the selection of the largest supply chain locations would not change significantly, and the weighting would be similar. The variation in this data is primarily between regions rather than over time; thus, the majority of the variation is captured despite the lack of annual data for all years.

As previously, noted, endogeneity has been a concern in examining power outages (Cole et al. 2018). For this reason, we sought out an instrumental variable to test for endogeneity. We explored a few variables, including the proportion of energy produced by hydroelectric generation, an instrument utilized by Cole et al. (2018). We used the Cragg-Donald Wald F statistic and Kleibergen-Paap rk Wald F statistic to test for weak identification (Stock and Yogo 2005; Greene 2008; Kleibergen and Paap 2006). Unfortunately, we did not find a suitable instrument (for power disturbances) for the test. The concern for endogeneity is that government policies and investments might affect both energy performance and firm performance. As discussed below, we use a fixed effects model, which aids in addressing this issue since we model impacts at the state level. We also include variables for state construction of electric utilities from the Annual Survey of State and Local Finances (U.S. Census 2020) and private nonresidential construction (U.S. Census 2021) to control for investments that may affect energy performance that could correlate with power disturbances and value added. A region that invests more is likely to have fewer outages and high value added. Including private nonresidential construction reduces the likelihood that we are identifying spurious or meaningless correlations with these investments rather than the effect of power disturbances. The model also includes analogous variables for the sum of government and private construction spending in the supply chain locations. To further address endogeneity, we also compare with results from a model with lagged variables for power. A variable for local power disturbances is included to ensure that the variable for supply chain impacts is not capturing local effects. The structural equation for the model in log terms is represented as the following:

$$
\begin{aligned}
\ln(VA_{i,t}) = {} & \beta_1 \ln(VA_{i,t-1}) + \beta_2 \ln(VA_{i,t-2}) + \beta_3 \ln(VA_{i,t-3}) + \beta_4 \ln(DIST_t) + \beta_5 \ln(SUPCHN_t) \\
& + \beta_6 NoDist_t + \beta_7 GOVCNST_{Loc,t-1} + \beta_8 PRIVCNST_{LOC,t-1} + \beta_9 GOVCNST_{SCHN,t-1} \\
& + \beta_{10} PRIVCNST_{SCHN,t-1} + \beta_{11} Q_2 + \beta_{12} Q_3 + \beta_{13} Q_4 + \alpha_i + \delta_t + \varepsilon_{it}
\end{aligned}
$$

[3] Note that, for the model, zero values (i.e., quarters with no power disturbances) were changed from zero to 0.000001 in order to be able to take the natural log of the values. A variable indicating no power disturbances was added to the model.

where

$$SUPCHN_t = \sum_{z=1}^{10} \frac{SC_{top-z,t}}{\sum_{i=1}^{50} SC_{i,t}} DIST_{top-z,t}$$

and where

$VA_{i,t}$ = Real value added (i.e., real gross domestic product) in 2012 chained dollars for industry i where $t-x$ indicates a lag of x quarters, and i is one of four industries: manufacturing, durable goods, nondurable goods, or total private industry. Note that the models of durable and nondurable goods includes an additional lag ($VA_{i,t-4}$).

$DIST_t$ = Total power disturbance in hours for time t.

δ_t = Quarterly fixed effect

$NoDist_t$= An indicator variable for no power disturbances at time t where $NoDist$ equals one if there are no power disturbances and zero otherwise.

$GOVCNST_{Loc,t-1}$ = Government construction of electric utilities from the Annual Survey of State and Local Finances (U.S. Census 2020) where Loc indicates the local value

$PRIVCNST_{LOC,t-1}$ = Private nonresidential construction from the Value of Construction Put in Place Survey (U.S. Census 2021) where Loc indicates the local value

$GOVCNST_{SCHN,t-1}$ = Government construction of electric utilities from the Annual Survey of State and Local Finances (U.S. Census 2020) where $SCHN$ indicates the sum of the top ten supply chain values

$PRIVCNST_{SCHN,t-1}$ = Private nonresidential construction from the Value of Construction Put in Place Survey (U.S. Census 2021) where $SCHN$ indicates the sum of the top ten supply chain values

Q_x = An indicator variable for quarter x where x is between 2 and 4.

SC_{top-z} = The z largest supply chain entity for the state based on shipments from one state to another where z is 1 through 10.

$DIST_{top-z}$ = Total power disturbance in the z largest supply chain entity for the state based on shipments from one state to another where z is 1 through 10.

SC_i = The total shipments originating from state i

β_x = The parameters to be estimated where x is 1 to 14

Note that although the parameters are estimated using linear regression, the relationship between the dependent variable and independent variable is not linear. The relationship is that of a Cobb-Douglas production function, as discussed above. The natural log of each side is taken to put the equation in a linear format to estimate parameters. Despite the linear format, the relationship is multiplicative and exponential.

As discussed in the results section, the local variables are not statistically significant; therefore, the results from a third model are presented. This model uses the model presented above excluding the variable for local power disturbances ($DIST_t$) and the indicator variable for no power disturbances ($NoDist_t$). This model is included for thoroughness and to confirm that the results for the variable for power outages in the supply chain remain largely unchanged.

The Akaike Information Criterion (AIC) was used to identify the number of lags to include to address autocorrelation (Akaike 1973), resulting in three to four lags of the dependent variable being included in the model. A test for heteroskedasticity using Stata, which includes three versions of the Breusch-Pagan (1979) and Cook-Weisberg (1983) test (Stata 2013a), was conducted. The results suggest that heteroskedasticity was present in the data. As a result, we fit a fixed-effects model using a "GLS estimator (producing a matrix-weighted average of the between and within results)" (Stata 2013b, Baltagi 2013, Wooldridge 2013). Previous research has shown that this approach can provide robust estimates for data with this issue (Hoechle 2007). It should be noted that a test presented by Hausman (1978) was used to determine whether a fixed effects or random effects model was more appropriate with the results suggesting a fixed effects model was preferred.

Given estimated model parameters, two simulations were run where the data was altered to forecast value added without any power disturbances. The model in the equation above is used, which excludes lagged variables for power disturbances but includes the local power disturbance variable. This simulation gives an indication as to the total losses associated with power disturbances. In the first simulation the local disturbance variable $DIST$ was set to 0.000001 and zero disturbance indicator $NoDist$ was set to one, which equates to zero power disturbances in the model. This measures the effect of power disturbances on those whose power was affected. Recall that zero values of $DIST$ were changed to a value of 0.000001 so that we could take the natural log of the variable and $NoDist$ was added to the model to account for zero values that were changed. In the second simulation, the supply chain variable $SUPCHN$ was set to one. Recall that $SUPCHN$ represents power outages in the supply chain. The simulations were ran for each of the four models. Using a bootstrapping procedure, the 95 % confidence intervals were calculated where the total impact is estimated for a random selection of observations. This process was iterated 5000 times in order to provide statistically representative results.

Finally, an investment analysis was conducted to examine what level of improvement in power disturbances would make a $50 billion investment economical. We examined four possibilities resulting from a $50 billion investment: 25 % reduction, 20 % reduction, 15 % reduction, and 10 % reduction in losses due to supply chain impacts. The net present value, internal rate of return, and payback period, as outlined in Thomas (2017), were used for the analysis. A modest 10-year study period, an annual 2 % decrease in the effect of the investment, and a 5 % discount rate were used. The 2 % decrease in the effect of the investment is used to account for degradation of equipment. A second set of analyses was conducted using the same variables but with a 20-year study period. A third set was examined with the 10-year study period but with a 5 % annual degradation of equipment. Finally, two additional investment analyses were conducted, which utilize direct losses from previously published research. One includes high estimate and one includes a low estimate of direct losses.

5. Results

Results for the regression analysis are shown in Table 5A with a version of the models with lagged power outage variables is presented in Table 5B and a version without local power disturbance shown in Table 5C. The results from Table 5A show that the local power outages were not statistically significant in any of the four models. The results from Table 5B show similar results and Table 5C shows similar results for power disturbances in the supply after removing the local power disturbance variables. A simulation was conducted where no power disturbances are simulated with the results shown in Table 6. The number of observations ranged between 2756 and 2764. The R^2 ranged between 0.9980 and 0.9998, which is high due to the inclusion of lagged dependent variables.

The variable for local power disturbances ($DIST$), which was used to control for local effects, was not statistically significant in any of the models; although, the no outage indicator variable was statistically significant and negative in one of the models. Previously published research suggests that power disturbances have a negative effect on GDP. Research on the U.S. has estimated direct losses to be between $19 billion and $255 billion, as seen in Table 8. Research for other locations include papers such as Andersen and Dalgaard (2013) who examined the effect of power outages in Sub-Saharan Africa and Das and McFarlane (2019) who examined losses to GDP in Jamaica. The U.S. likely has lower levels of power disturbance; thus, our statistical study might not detect the local negative impacts on value added due to the lower level of disruption. Another reason for the lack of significance might be data resolution, as we examine quarterly losses at the state level. If disruptions are concentrated in time and space, areas with lower levels of disruption can obscure the impacts of outages. It is also important to note that power outages are often the result of natural hazards, which can induce post-event spending (e.g., relief funds) that can increase value added and obscure the impact of the hazard. Moreover, there are a number of reasons why a statistical model, such as ours, might not detect a decrease in value added locally due to power outages. Given that the results discussed below suggest there are downstream supply chain impacts from power outages and given the results from other studies, it is likely that there are local impacts that are not detected. For this reason, other approaches (e.g., VoLL) might be more appropriate for measuring direct short-term losses (i.e., top row middle column of Table 2)..

The variable for power disturbances in the supply chain ($SUPCHN$) was statistically significant at the 0.01 level and negative in all four models shown in Table 5A. The elasticity for this variable ranged between -0.0092 and -0.0023 with the 95 % confidence intervals ranging between -0.0111 and -0.0015, as seen in Table 5A. The simulation results estimate that eliminating power disturbances in the supply chain can increase value added by between 0.8 % and 3.3 %; however, the 95 % confidence intervals range into negative values. When using lagged power disturbances, only the supply chain variable for durable goods for power disturbances was statistically significant (see Table 5B). Using lagged power outage variables assumes that the lagged variable serves as a good proxy for outages, which may or may not be the case. The effect of power disturbances might, for instance, stretch into the quarter following the power disturbance to make the lagged variable a good proxy. Since disturbances are often short term and relatively low impact (compared to, for instance, major natural disasters), the effect of these events may not extend that far for all industries. We explored the option of lagged power outage variables to address concerns regarding endogeneity and included the results to be thorough.

This analysis tested four hypotheses with all four being confirmed (i.e., the statistical models failed to reject the null hypothesis of no association), corresponding to supply chain impacts from power disturbances, as shown in Table 7. The results as they relate to the hypotheses are discussed below.

Supply Chain Impact on Value Added: The hypothesis statements are in regard to power disturbances locally reducing value added in the supply chain: Hypothesis 1 regarding manufacturing value added; Hypothesis 2 regarding durable goods value added; Hypothesis 3 regarding nondurable goods value added; and Hypothesis 4 regarding private industry value added. All four of these hypotheses were supported by the models through the statistical significance of the variable measuring power disturbances in the supply chain ($SUPCHN$), which was significant at the 0.01 level for all four models. The elasticities for the model of manufacturing value added, durable goods value added, nondurable goods value added, and private industry value added were -0.0065, -0.0041, -0.0092, and -0.0023 respectively. This means, for instance, that for every 1 % increase in outages in the supply chain, there is a -0.0065 % change in manufacturing value added.

The lack of studies on the short-term downstream impacts and the varying factors from other studies make it difficult to compare our findings to others. For instance, Major (2015) found that a 2.08 % decrease in energy supply results in a 0.53 % decrease in GDP in Hungary. It also uses a computable general equilibrium model, which does not incorporate the immediate effects of a loss of power such as disorganization and the failure of goods to arrive on time at the factory floor. Our paper examined hours of outage rather than percent energy losses. We also used a correlation study rather than a CGE model. We find that a 1 % decrease in hours of outage results in an increase in private GDP by 0.0023 % indirectly through the downstream supply chain. Adbasi (2018) studies productivity impacts on firms in Ethiopia and finds that power outages increase firm costs by 15 %. This metric, however, is not easily comparable to our metrics or those of other papers. It is also important to note that the research also varies by country and economy type, which makes direct comparisons of limited value. Moreover, translating to common metrics/values and comparing the findings of the current literature might constitute a study in and of itself. Additionally, these papers do not examine the downstream short-run losses that are measured in this paper.

Simulation: Two simulations were run where the data was altered to forecast value added without any power disturbances, which gives an indication as to the total losses associated with power disturbances. The results suggest that eliminating power outages increases manufacturing value added, durable goods value added, nondurable goods value added, and private industry value added by 2.3 % ($49.0 billion in 2016), 1.5 % ($17.3 billion in 2016), 3.3 % ($30.3 billion in 2016), and 0.8 % ($133.1 billion in 2016).

Our findings suggest that the supply chain may contain a large share of the economic impact when compared to the losses estimated in other papers (see Table 8). Even supplies of relatively small items can have a big impact downstream. For instance, significant delays in production of the Boeing 787 Dreamliner were due to a shortage of fasteners (i.e., bolts). Bolts/fasteners for airplanes are unique in that they are aluminum and titanium, but their value is small compared to that of the 787 production (Reuters 2007). Additionally, the disruption of an individual supplier is likely to affect multiple customers, where the aggregate effect on the customers might exceed the effect on the supplier. For instance, the shortage of fasteners likely affected production of aircraft other than the 787. Thus, it is plausible for the downstream impact to exceed the direct impact.

Loss estimates from literature, which is summarized in Table 8, range from $19 billion to $255 billion. The results from this paper suggest a large additional loss in GDP results from power outages in the short-term downstream supply chain. This creates a significant disconnect between the stakeholder that invests in reliability in the power grid and the stakeholders that experience the bulk of losses. This situation can easily result in under investment in reliability that diminishes GDP. To put the impact in perspective, the estimated $49.0 billion loss in the manufacturing industry equates to being in the top 5 % of costs listed in NIST's Manufacturing Cost Guide (Thomas 2020, Thomas 2019). While manufacturing represents 12.8 % of private industry value added, it experiences 36.8 % of the supply chain losses due to power disturbances, as suggested by the results of the simulation. The disproportional impact estimated for manufacturing is plausible given that manufacturing relies more heavily on the timely delivery of supplies than other industries. For instance, a retail store can continue to sell goods for quite some time even if a shipment is late; however, manufacturers need supplies to continue operations, especially given the emphasis on lean production where inventories are minimized as much as possible in order to reduce costs. The evidence suggests that investing in energy resilience will make the U.S. manufacturing industry more competitive along with doing the same for total private industry. The estimated total $133.1 billion loss of private industry value added is an annual loss estimate, meaning an increase in energy resilience would result in annual gains of as much as $133.1 billion. This does not include all benefits, such as the impact to private households or direct impacts.

Investment Analysis: To examine the return on investing in energy resilience, we can run some investment scenarios. Consider the effect of a $50 billion investment in energy resilience on private industry. Note that we do not know the percent reduction it might have on private losses, but we can consider various possibilities. In this instance, we investigate four possibilities resulting from a $50 billion investment: 25 % reduction, 20 % reduction, 15 % reduction, 10 % reduction, and 5 % reduction in losses due to supply chain impacts. We will use the methods outlined in Thomas (2017) along with two different study periods (10 year and 20 year), two different annual rates of degradation (2 % and 5 %) on the effect of the investment, and a 5 % discount rate. As seen in Table 9, most of the scenarios are economical except for two scenarios where the decrease in losses is only 5 %. The last two sets of analyses in Table 9 include reductions in the highest (i.e., $255 billion) and lowest (i.e., $19 billion) direct losses from Table 8. All of the scenarios in these two sets were found to be economical.

It is important to note that in our literature review we did not identify any studies that estimate the total impact of power outages nor does our study. That is, no study fit into all six boxes in Table 2. Moreover, to estimate the total impact, multiple approaches are needed.

7. Conclusion

This paper measures the economic impact of power disturbances on value added for manufacturing, durable goods, nondurable goods, and total private industry using regression analysis. The model includes a variable for power disturbances occurring locally and one for those states in the top 20 % of the supply chain for a given location. All four hypotheses examined in this paper were supported by the models. Moreover, the results suggest that power disturbances have a statistically significant effect on value added in the downstream supply chain for manufacturing, durable goods, nondurable goods, and the private industry. The results also suggest that the supply chain impact could be similar to or larger than the local impact. The supply chain impact was statistically significant with the 95 % confidence interval for the elasticity ranging between -0.0111 and -0.0015. Moreover, the evidence is fairly robust in showing that there is a negative effect from disturbances in the supply chain.

Depending on the industry, the simulation results suggest between a 0.8 % and 3.3 % increase in value added in the absence of disturbances, which amounts to $49.0 billion in manufacturing and $133.1 billion in total private industry; however, the 95 % confidence interval for the simulation ranges from negative values to positive values. Thus, the evidence for the total magnitude of the impact is less certain. More confident estimates of the magnitude of the effect require additional research and/or more precise data collection. The data specifies the duration of power disturbances; however, the extent of the disturbance (e.g., the number of customers affected) is often unclear. The geographic areas are also quite large, being at the state level. Sometimes, one disturbance lists multiple states. More detailed geographic information, such as county level observations, might bring more precision in measuring the magnitude of the impact.

In our literature review, we did not identify research that covered all loss types described in Table 2. Thus, a comprehensive estimate likely requires using multiple approaches. For instance, VoLL might be used for estimating direct short-term losses. CGE models might be used to estimate upstream and long-term losses and econometric models used for estimating downstream short-term losses.

Future research might aim to increase precision in understanding the magnitude of the impacts resulting from power disturbances. Data could be collected from manufacturers asking if they have experienced power disturbances and what the effects were experienced. This paper examined the impact of power disturbances occurring locally and occurring in the tier 1 supply chain. Future research could examine tier 2 effects and beyond along with the effects of power disturbances downstream.

Bibliography

Abeberese, A. B., Ackah, C. G., & Asuming, P. O. (2018). Productivity Losses and Firm Responses to Electricity Shortages: Evidence from Ghana. The World Bank Economic Review. https://doi.org/10.1093/wber/lhz027.

Abrate, G., Bruno, C., Erbetta, F., Fraquelli, G., & Lorite-Espejo, A. (2016). A choice experiment on the willingness of households to accept power outages. Utilities Policy 43(B), 151-164. https://doi.org/10.1016/j.jup.2016.09.004.

Adbasi, L. (2018). Power outages, economic cost, and firm performance: Evidence from Ethiopia. Utilities Policy 53, 111-120. https://doi.org/10.1016/j.jup.2018.06.009.

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In Second International Symposium on Information Theory, ed. B. N. Petrov and F. Csaki, 267–281. Budapest: Akailseoniai–Kiud

Alcott, H., Collard-Wexler, A., & O'Connell, S.D. (2016). How do electricity shortages affect industry? Evidence from India. American Economic Review 106(3), 587-624. https://dx.doi.org/10.1257/aer.20140389.

Andresen, T.B., & Dalgaard, C. 2013. Power outages and economic growth in Africa. Energy Economics 38, 19-23. http://dx.doi.org/10.1016/j.eneco.2013.02.016.

Baltagi, B. H. (2013). Econometric Analysis of Panel Data· 5th ed. Chichester, UK: Wiley

Breusch, T. S., and A. R. Pagan. (1979). A simple test for heteroscedasticity and random coefficient variation. Econometrica 47: 1287–1294.

Bureau of Economic Analysis. 2020. Real GDP by State. https://apps.bea.gov/iTable/index_regional.cfm

Campbell, Richard J. (2012). "Weather-Related Power Outages and Electric System Resiliency." Congressional Research Service. https://www.ourenergypolicy.org/wp-content/uploads/2016/02/R42696.pdf

Carlsson, F., Demeke, E., Martinsson, P., & Tesemma, T. 2020. Cost of power outages for manufacturing firms in Ethiopia: A stated preference study. Energy Economics 88, 104753. https://doi.org/10.1016/j.eneco.2020.104753.

Castro, R., Faias, S., & Esteves, J. (2016). The cost of electricity interruptions in Portugal: Valuing lost load by applying the production-function approach. Utilities Policy 40, 48-57. https://doi.org/10.1016/j.jup.2016.04.003.

Cole, M.A., Elliott, R.J.R., Occhiali, G., & Strobl, E. (2018). Power outages and firm performance in Sub-Saharan Africa. Journal of Development Economics 134, 150-159. https://doi.org/10.1016/j.jdeveco.2018.05.003.

Coll-Mayor, D., Pardo, J., & Perez-Donsion, M. (2012). Methodology based on the value of lost load for evaluating economical losses due to disturbances in the power quality. Energy Policy 50, 407-418. http://dx.doi.org/10.1016/j.enpol.2012.07.036.

Cook, R. D., and S. Weisberg. 1983. Diagnostics for heteroscedasticity in regression. Biometrika 70: 1–10.

Das, A. & McFarlane, A. (2019). Non-linear dynamics of electric power losses, electricity consumption, and GDP in Jamaica. Energy Economics 84, 104530. https://doi.org/10.1016/j.eneco.2019.104530.

Department of Energy. 2020. Electric Disturbance Events (OE-417) Annual Summaries. https://www.oe.netl.doe.gov/OE417_annual_summary.aspx

Diboma, B.S., & Tatieste, T.T. (2013). Power interruption costs to industries in Cameroon. Energy Policy 62, 582-592. https://doi.org/10.1016/j.enpol.2013.07.014.

Edison International (2016). "8 Common Causes of Outages." https://energized.edison.com/stories/8-common-causes-of-outages

Energy Information Administration (2020a). Annual Electric Power Industry Report, Form EIA-861 detailed data files. https://www.eia.gov/electricity/data/eia861/

Energy Information Administration (2020b). "How electricity is delivered to consumers." https://www.eia.gov/energyexplained/electricity/delivery-to-consumers.php

Energy Information Administration (2021). "Monthly Generation Data by State, Producer Sector and Energy Source." EIA 923 Report. https://www.eia.gov/electricity/data.php#generation

Fallahi, Firouz, (2011). "Causal relationship between energy consumption (EC) and GDP: A Markov-switching (MS) causality," Energy, Elsevier, vol. 36(7), pages 4165-4170.

Fisher-Vanden, K., Mansur, E.T., & Wang, Q. (2015). Electricity shortages and firm productivity: Evidence from Ch'na's industrial firms. Journal of Development Economics 114, 172-188. https://doi.org/10.1016/j.jdeveco.2015.01.002.

Fried, S., & Lagakos, D. (2020). Electricity and Firm Productivity: A General-Equilibrium Approach. National Bureau of Economic Research, Working Paper 27081. https://www.nber.org/papers/w27081.

Ghosh, R., Goyal, Y., Rommel, J., & Sagebiel, J. (2017). Are small firms willing to pay for improved power supply? Evidence from a contingent valuation study in India. Energy Policy 109, 659-665. https://doi.org/10.1016/j.enpol.2017.07.046.

Grainger, C., & Zhang, F. (2019). Electricity shortages and manufacturing productivity in Pakistan. Energy Policy 132, 1000-1008. https://doi.org/10.1016/j.enpol.2017.07.046.

Greene, William H. (2008). Econometric Analysis. 6th Edition. Pearson Education Inc. Upper Saddle River, NJ. (377-380)

Guha, Gauri S. 2005. "Simulation of the Economic Impact of Regionwide Electricity Outages from a Natural Hazard Using a CGE Model." Southeastern Economic Review 32 (1), Spring: 101-124.

Hausman, J. A. (1978). Specification tests in econometrics. Econometrica 46: 1251–1271.

Hines, P., Apt, J., and Talukdar, S., (2008). "Trends in the history of large blackouts in the United States," 2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, Pittsburgh, PA, USA, pp. 1-8, doi: 10.1109/PES.2008.4596715.

Ho, C.Y. & Siu, K.W. (2007). A dynamic equilibrium of electricity consumption and GDP in Hong Kong: An empirical investigation. Energy Policy 35(4), 2507-2513. https://doi.org/10.1016/j.enpol.2006.09.018

Hoechle, D. 2007. Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence. The Stata Journal, 7(3), 281-312.

Huang, B.N., Hwang, M.J., & Yang, C.W. (2008). Causal relationship between energy consumption and GDP growth revisited: A dynamic panel data approach. Ecological Economics 67(1), 41-54. https://doi.org/10.1016/j.ecolecon.2007.11.006

Kim, K., & Cho, Y. (2017). Estimation of power outage costs in the industrial sector of South Korea. Energy Policy 101, 236-245. https://doi.org/10.1016/j.enpol.2016.11.048.

Kleibergen, F. and Paap, R. (2006). "Generalized Reduced Rank Tests Using the Singular Value Decomposition." Journal of Econometrics, Vol. 133, pp. 97-126.

LaCommare, Kristina Hamachi, and Joseph H. Eto. (2006) "Cost of Power Interruptions to Electricity Consumers in the United States." Energy, Vol. 31.

Larsen, P.H., Boehlert, B., Eto, J., Hamachi-LaCommare, K., Martinich, J., & Rennels, L. (2018). Projecting future costs to U.S. electric utility customers from power interruptions. Energy 147, 1256-1277. https://doi.org/10.1016/j.energy.2017.12.081.

Linares, P., & Rey, L. (2013). The costs of electricity interruptions in Spain. Are we sending the right signals? Energy Policy 61, 751-760. https://doi.org/10.1016/j.enpol.2013.05.083.

Major, Klara. (2015). “Macroeconomic impact of electric power outage – simulation results from a CGE modelling experiment for Hungary.” Hetfa Research Institute. http://hetfa.eu/wp-content/uploads/2016/01/HETFA_WP_impact_of_power_outage.pdf

Mohan, P.S., Spencer, N. & Strobl, E. 2019. Natural Hazard-Induced Disasters and Production Efficiency: Moving Closer to or Further from the Frontier?. Int J Disaster Risk Sci 10, 166–178. https://doi.org/10.1007/s13753-019-0218-9.

Moyo, B. (2013). Power infrastructure quality and manufacturing productivity in Africa: A firm level analysis. Energy Policy 61, 1063-1070. https://doi.org/10.1016/j.enpol.2013.05.111.

Mukherjee, S., Nateghi, R., & Hastak, M. (2018). A multi-hazard approach to assess severe weather-induced major power outage risks in the U.S. Reliability Engineering and System Safety 175, 283-305. https://doi.org/10.1016/j.ress.2018.03.015

Niroomand, N., & Jenkins, G.P. (2020). Estimation of househo’ds' and busines’es' willingness to pay for improved reliability of electricity supply in Nepal. Energy for Sustainable Development 55, 201-209. https://doi.org/10.1016/j.esd.2020.02.006.

Oseni, M.O. & Pollitt, M.G. (2015). A firm-level analysis of outage loss differentials and self-generation: Evidence from African business enterprises. Energy Economics 52, 277-286. https://doi.org/10.1016/j.eneco.2015.11.008.

Ozbafli, A. & Jenkins, G.P. (2016). Estimating the willingness to pay for reliable electricity supply: A choice experiment study. Energy Economics 56, 443-452. https://doi.org/10.1016/j.eneco.2016.03.025.

Pepermans, G. (2011). The value of continuous power supply for Flemish households. Energy Policy 39, 7853-7864.

President’s Council of Economic Advisers and U.S. Department of Energy’s Office of Electricity Delivery and Energy Reliability. (2013). “Economic Benefits of Increasing Electric Grid Resilience to Weather Outages.” https://www.energy.gov/sites/prod/files/2013/08/f2/Grid%20Resiliency%20Report_FINAL.pdf

Primen. (2001). “The Cost of Power Disturbances to Industrial and Digital Economy Companies.” TR1006274 (Available through EPRI).

PwC (2015). “Do you Know where your Supply Chain is?” https://www.pwc.com/us/en/services/allianc17thisphereere/supply-chain.html

Reuters. “Boeing CEO blames industry for 787 bolt shortage.” September 11, 2007. https://www.reuters.com/article/us-boeing-alcoa/boeing-ceo-blames-industry-for-787-bolt-shortage-idUSN1141086620070911

Rose, Adam, and Gbadebo Oladosu, Derek Salvino. 2005. “Economic Impacts of Electricity Outages in Los Angeles: The Importance of Resilience and General Equilibrium Effects.” In M. A. Crew and M. Spiegel, Eds., , Obtaining the Best from Regulation and Competition. Springer Science.

Rose, Adam, and Gbadebo Oladosu, Shu-Yi Liao. 2007. "Business Interruption Impacts of a Terrorist Attack on the Electric Power System of Los Angeles: Customer Resilience to a Total Blackout." Risk Analysis 27 (3): 513-531.

Rose, Adam, and Juan Benavides, Stephanie E. Chang, Philip Szczesniak, Dongsoon Lim. 1997. "The Regional Economic Impact of An Earthquake: Direct and Indirect Effects of Electricity Lifeline Disruptions." Journal of Regional Science 37 (3): 437-458.

S&C Electric Company. (2018). S&C's 2018 State of Commercial & Industrial Power Reliability Report. https://www.sandc.com/globalassets/sac-electric/documents/sharepoint/documents---all-documents/technical-paper-100-t120.pdf?dt=637518043999116077

Serra, P. & Fierro, G. (1997). Outage costs in Chilean industry. Energy Economics 19(4), 417-434. https://doi.org/10.1016/S0140-9883(97)01017-7.

Shuai, M., Chengzhi, W., Shiwen, Y., Hao, G., Jufang, Y., & Hui, H. (2018). Review on Economic Loss Assessment of Power Outages. Procedia Computer Science 130, 1158-1163. https://doi.org/10.1016/j.procs.2018.04.151.

Stata. 2013a. "Regress Postestimation." Stata User's Guide: Release 13. https://www.stata.com/manuals13/rregresspostestimation.pdf

Stata. 2013b. "Xtreg." Stata User's Guide: Release 13. https://www.stata.com/manuals13/xtxtreg.pdf

Stock, J.H. and Yogo, M. (2005). "Testing for Weak Instruments in Linear IV Regression." In D.W.K. Andrews and J.H. Stock, eds. Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg. Cambridge: Cambridge University Press, 2005, pp. 80�108. Working paper version: NBER Technical Working Paper 284. http://www.nber.org/papers/T0284.

Swaminathan, S., and R. K. Sen. (1997) "Review of Power Quality Applications of Energy Storage Systems." Sandia National Laboratories.

Thomas, Douglas S. (2017). "Investment Analysis Methods: A practitioner's guide to understanding the basic principles for investment decisions in manufacturing." NIST AMS 200-5. https://doi.org/10.6028/NIST.AMS.200-5

Thomas, Douglas S. (2019). "Manufacturing Cost Guide." Version 1.0. https://www.nist.gov/services-resources/software/manufacturing-cost-guide

Thomas, Douglas S. (2020). "Annual Report on U.S. Manufacturing Industry Statistics: 2020." https://doi.org/10.6028/NIST.AMS.100-37

Ugur, Mehmet, Trushin, Eshref, Solomon, Edna, and Guidi, Francesco. "R&D and Productivity in OECD Firms and Industries: A Hierarchical Meta-Regression Analysis." Research Policy. 45 (2016): 2069-2086.

U.S. Census Bureau. (2020). Annual Survey of State and Local Government Finances. https://www.census.gov/programs-surveys/gov-finances.html

U.S. Census Bureau. (2021). Value of Construction Put in Place Survey. https://www.census.gov/construction/c30/c30index.html

Sue Wing, Ian and Rose, Adam. (2018) “Economic Consequence Analysis of Electric Power Infrastructure Disruptions: An Analytical General Equilibrium Approach.” http://dx.doi.org/10.2139/ssrn.3276978

Wooldridge, J. M. (2013). Introductory Econometrics: A Modern Approach. 5th ed. Mason, OH: South-Western.

Wolf, A., & Wenzel, L. (2016). Regional diversity in the costs of electricity outages: Results for German counties. Utilities Policy 43(B), 195-205. https://doi.org/10.1016/j.jup.2014.08.004.

Woo, C.K., Ho, T., Shiu, A., Cheng, Y.S., Horowitz, I., & Wang, J. (2014) Residential cost outage estimation: Hong Kong. Energy Policy 72, 204-210. https://doi.org/10.1016/j.enpol.2014.05.002.

Zachariadis, T., & Poullikkas, A. (2012). The costs of power outages: A case study from Cyprus. Energy Policy 51, 630-641. http://dx.doi.org/10.1016/j.enpol.2012.09.015.

Table 1: Frequency and Disruption (MW) of Blackouts by Cause Category

	A Percent of events	B Mean size in MW	C Mean size in customers	D=A×B Risk Metric 1	E=A×C Risk Metric 2
Wind/rain	14.8	793	185 199	117	27 409
Equipment failure	29.7	379	57 140	113	16 971
Ice storm	5	1 152	343 448	58	17 172
Hurricane/tropical storm	4.2	1 309	782 695	55	32 873
Operator error	10.1	489	105 322	49	10 638
Other external cause	4.8	710	246 071	34	11 811
Lightning	11.3	270	70 944	31	8 017
Other cold weather	5.5	542	150 255	30	8 264
Fire	5.2	431	111 244	22	5 785
Supply shortage	5.3	341	138 957	18	7 365
Voltage reduction	7.7	153	212 900	12	16 393
Earthquake	0.8	1 408	375 900	11	3 007
Volunteer reduction	5.9	190	134 543	11	7 938
Tornado	2.8	367	115 439	10	3 232
Intentional attack	1.6	340	24 572	5	393

Data Source: Hines, P., Apt, J., and Talukdar, S., "Trends in the history of large blackouts in the United States," 2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, Pittsburgh, PA, USA, 2008, pp. 1-8, doi: 10.1109/PES.2008.4596715.

Note: Percentages do not add to 100 % because some records fall into multiple initiating-event categories.

Table 2: Literature on Economic Impacts of Electricity Disruption by Time of Loss and Supply Chain Point

		Supply Chain Point of Loss		
Time of Loss		Upstream	Direct	Downstream
	Short Term	IDENTIFIED METHODS: CGE Models, Input-Output Models IDENTIFIED LITERATURE: Fried and Lagakos 2020; Rose et al 2005; Rose et al. 1997; Rose et al. 2007; Guha 2005; Wing and Rose 2018	IDENTIFIED METHODS: Direct loss, VoLL, production functions, econometric models IDENTIFIED LITERATURE: Castro et al. 2016; Linares and Rey 2013; Serra and Fierro 1997; Diboma and atieste 2013; Kim and Cho 2017; Oseni and Pollitt 2015; Woo et al. 2014; Linares and rey 2013; Castro et al. 2016; Wolf and Wenzel 2016; Zachariadis and Poullikas 2012; Moyo 2013; Adbasi 2018; Fisher-Vanden et al. 2015; Granger adn Zhang 2019; Cole et al. 2018; ALam 2013; Alcott et al 2016; Abeberese et al. 2019; Coll-Mayor et al. 2012; Andersen and Dalgaard 2013; Das and McFarlane 2019; Niroomand adn Jenkins 2020; Ozbafli and Jenkins 2016; Carlsson et al. 2011; Pepermans 2011; Abrate et al. 2016; Primen 2001; LaCommare and Eto (2006); Swaminathan and Sen (1997); Campbell (2012); President's Council of Economic Advisers et al. (2013)	★
	Long Term	IDENTIFIED METHODS: CGE Models IDENTIFIED LITERATURE: Fried and Lagakos 2020; Rose et al 2005; Rose et al. 2007; Guha 2005; Wing and Rose 2018	IDENTIFIED METHODS: CGE models, econometric models, other forecasting models IDENTIFIED LITERATURE: Larsen et al 2018; Fried and Lagakos 2020; Andersen and Dalgaard 2013; Das and McFarlane 2019; Rose et al 2005; Rose et al. 1997; Rose et al. 2007; Guha 2005; Wing and Rose 2018	IDENTIFIED METHODS: CGE Models IDENTIFIED LITERATURE: Fried and lagakos 2020; Rose et al 2005; Rose et al. 2007; Guha 2005; Wing and Rose 2018

★ The topic area of this paper

Table 3: Data Summary

Year	Manufacturing GDP	Durable Goods GDP	Nondurable Goods GDP	Private Industry GDP	Average of Disturbance duration in Hours	Range of Disturbance Duration in Hours	Average of Supply Chain Variable	Range of Supply Chain Variable
2005	37 306.9	17 497.1	20 250.5	254 524.1	38.2	0 - 1110.8	37.7	1.7 - 150
2006	39 319.2	18 802.9	20 832.3	262 756.7	36.6	0 - 1344.9	40.2	4 - 266.9
2007	40 537.3	19 654.3	21 177.1	267 100.9	15.4	0 - 327.9	21.5	0.4 - 100.4
2008	39 649.7	19 727.2	20 027.3	265 466.1	51.5	0 - 1652.1	80.9	7 - 757.4
2009	35 946.1	16 832.4	19 427.1	257 454.1	45.1	0 - 1374.7	64.1	0.9 - 400.2
2010	37 954.3	18 969.4	19 116.5	264 122.3	31.3	0 - 490.7	51.8	4.1 - 221
2011	38 038.8	20 252.9	17 799.0	268 585.6	63.5	0 - 821.3	87.1	10.6 - 341.8
2012	37 785.3	20 817.8	16 967.5	275 245.4	52.8	0 - 828.8	53.9	2.3 - 377.6
2013	38 946.0	21 331.6	17 616.8	280 440.7	52.6	0 - 3358.7	74.2	1.6 - 544.1
2014	39 613.1	21 647.0	17 956.2	288 559.6	45.3	0 - 1925.8	46.6	2.2 - 491.3
2015	40 171.2	22 075.4	18 106.8	298 864.6	16.7	0 - 427.8	25.7	0.6 - 173.2
2016	39 846.2	22 051.9	17 803.5	304 217.8	20.3	0 - 688.7	41.4	1.3 - 233.1
2017	42 506.0	23 725.1	18 801.5	311 887.5	20.6	0 - 1041.8	52.4	1.9 - 410.4
2018	42 629.0	23 905.2	18 754.8	321 989.1	38.8	0 - 1514	56.5	3.3 - 530.1
2019	43 483.8	24 282.1	19 234.5	329 666.1	24.6	0 - 447.1	43.3	7.4 - 183.9
2020	40 872.1	22 452.9	18 455.4	312 246.3	24.2	0 - 105.7	23.7	5.4 - 43.9

Data Sources: Bureau of Economic Analysis. 2020. Real GDP by State. https://apps.bea.gov/iTable/index_regional.cfm
Department of Energy. 2020. Electric Disturbance Events (OE-417) Annual Summaries.
https://www.oe.netl.doe.gov/OE417_annual_summary.aspx

Table 4: Models and Hypotheses

		Dependent Variable (value added)			
		Manufacturing	Durable Goods	Nondurable Goods	Private Industry
Independent Variables	2nd Quarter Indicator	X	X	X	X
	3rd Quarter Indicator	X	X	X	X
	4th Quarter Indicator	X	X	X	X
	Manufacturing GDP Lagged 1, 2, and 3 Quarters	X			
	Durable Goods GDP Lagged 1, 2, 3, and 4 Quarters		X		
	Nondurable Goods GDP Lagged 1, 2, 3, and 4 Quarters			X	
	Private Industry GDP Lagged 1, 2, and 3 Quarters				X
	Hours of Disturbance	X	X	X	X
	No Disturbance Indicator	X	X	X	X
	State Government Construction	X	X	X	X
	Private Construction	X	X	X	X
	State Government Construction Supply Chain	X	X	X	X
	Private Construction Supply Chain	X	X	X	X
	Supply Chain Disturbance	X	X	X	X
Hypotheses	1. Power Disturbances in the supply chain reduce manufacturing value added locally.	X			
	2. Power Disturbances in the supply chain reduce durable goods value added locally.		X		
	3. Power Disturbances in the supply chain reduce nondurable goods value added locally.			X	
	4. Power Disturbances in the supply chain reduce private industry value added locally.				X

Table 5A: Results of Analysis, Elasticities

	Manufacturing	Durable Goods	Nondurable Goods	Private Industry
2nd Quarter Indicator (Q_2)	0.0086***	0.0088***	0.0088***	0.0011
3rd Quarter Indicator (Q_3)	0.0046**	0.0131***	-0.0036	0.0005
4th Quarter Indicator (Q_4)	0.0065***	0.0084***	0.0030	0.0010
Manufacturing VA Lagged 1 Quarter ($VA_{man,t-1}$)	1.1149***			
Manufacturing VA Lagged 2 Quarters ($VA_{man,t-2}$)	-0.0473			
Manufacturing VA Lagged 3 Quarters (VAman,t-3)	-0.1776***			
Durable Goods VA Lagged 1 Quarter (VADur,t-1)		1.1393***		
Durable Goods VA Lagged 2 Quarters (VADur,t-2)		-0.0013		
Durable Goods VA Lagged 3 Quarters (VADur,t-3)		-0.3032***		
Durable Goods VA Lagged 4 Quarters (VADur,t-4)		0.0791***		
Nondurable Goods VA Lagged 1 Quarter ($VA_{NonDur,t-1}$)			1.0248***	
Nondurable Goods VA Lagged 2 Quarters ($VA_{NonDur,t-2}$)			0.0089	
Nondurable Goods VA Lagged 3 Quarters (VANonDur,t-3)			-0.1704***	
Nondurable Goods VA Lagged 4 Quarters (VANonDur,t-4)			0.0374	
Private Industry VA Lagged 1 Quarter (VAPriv,t-1)				1.0544***
Private Industry VA Lagged 2 Quarters (VAPriv,t-2)				0.0124
Private Industry VA Lagged 3 Quarters (VAPriv,t-3)				-0.0784***
State Government Construction (GOVCNSTLoc,t-1	0.0021	-0.0007	0.0058	0.0001
Private Construction (PRIVCNSTLOC,t-1)	-0.0050	-0.0049**	-0.0018	-0.003**
State Government Construction Supply Chain (GOVCNSTSCHN,t-1)	<0.0001	0.0001	0.0008	<0.0001
Private Construction Supply Chain (PRIVCNSTSCHN,t-1)	0.0138***	0.0044	0.0179***	0.0007
Hours of Outage (DISTt)	-0.0008	-0.0008	-0.0009	-0.0003
95 % confidence interval	*-0.0020*	*-0.0021*	*-0.0024*	*-0.0007*
	0.0003	*0.0004*	*0.0007*	*0.0001*
No Outage Indicator (NoDistt)	-0.0187*	-0.0174	-0.0201	-0.0056
Supply Chain Outage (SUPCHNt)	-0.0065***	-0.0041***	-0.0092***	-0.0023***
95 % confidence interval	*-0.0079*	*-0.0067*	*-0.0111*	*-0.0031*
	-0.0052	*-0.0015*	*-0.0074*	*-0.0015*
Constant	0.9974***	0.7964***	0.7436***	0.1667**
sigma_u	0.1450	0.1293	0.1293	0.0157
sigma_e	0.0355	0.0382	0.0526	0.0139
rho	0.9436	0.9199	0.8579	0.5589

* Statistically significant at the 0.10 level

** Statistically significant at the 0.05 level

*** Statistically significant at the 0.01 level

Note: VA=Value Added, Dur=Durable Goods, NonDur=Nondurable Goods, Priv=Private Industry

Table 5B: Results of Analysis, Elasticities (lagged power outage variables)

	Manufacturing	Durable Goods	Nondurable Goods	Private Industry
2nd Quarter Indicator (*Q_2*)	0.0112***	0.0105***	0.0123***	0.0019**
3rd Quarter Indicator (*Q_3*)	0.0054***	0.0128***	-0.0014	0.0006
4th Quarter Indicator (*Q_4*)	0.0065***	0.0079***	0.0034*	0.0009
Manufacturing VA Lagged 1 Quarter ($VA_{man,t-1}$)	1.1279***			
Manufacturing VA Lagged 2 Quarters ($VA_{man,t-2}$)	-0.0560			
Manufacturing VA Lagged 3 Quarters ($VA_{man,t-3}$)	-0.1809***			
Durable Goods VA Lagged 1 Quarter ($VA_{Dur,t-1}$)		1.1439***		
Durable Goods VA Lagged 2 Quarters ($VA_{Dur,t-2}$)		-0.0059		
Durable Goods VA Lagged 3 Quarters ($VA_{Dur,t-3}$)		-0.3099***		
Durable Goods VA Lagged 4 Quarters ($VA_{Dur,t-4}$)		0.0867***		
Nondurable Goods VA Lagged 1 Quarter ($VA_{NonDur,t-1}$)			1.0398***	
Nondurable Goods VA Lagged 2 Quarters ($VA_{NonDur,t-2}$)			0.0029	
Nondurable Goods VA Lagged 3 Quarters ($VA_{NonDur,t-3}$)			-0.1935***	
Nondurable Goods VA Lagged 4 Quarters ($VA_{NonDur,t-4}$)			0.0510**	
Private Industry VA Lagged 1 Quarter ($VA_{Priv,t-1}$)				1.0629***
Private Industry VA Lagged 2 Quarters ($VA_{Priv,t-2}$)				0.0155
Private Industry VA Lagged 3 Quarters ($VA_{Priv,t-3}$)				-0.0907***
State Government Construction ($GOV_{CNSTLoc,t-1}$)	0.0022	-0.0007	0.0059	0.0002
Private Construction ($PRIVCNST_{LOC,t-1}$)	-0.0046	-0.0047**	-0.0013	-0.0028**
State Government Construction Supply Chain ($GOVCNST_{SCHN,t-1}$)	0.0001	0.0001	0.0009	<0.0001
Private Construction Supply Chain ($PRIVCNST_{SCHN,t-1}$)	0.0147***	0.0045	0.0197***	0.0009
Hours of Outage ($DIST_{t-1}$)	-0.0003	-0.0005	<0.0001	-0.0003
95 % confidence interval	*-0.0013*	*-0.0017*	*-0.0013*	*-0.0006*
	0.0008	*0.0008*	*0.0014*	*0.0001*
No Outage Indicator ($NoDist_{t-1}$)	-0.0059	-0.0111	0.0031	-0.0063**
Supply Chain Outage ($SUPCHN_{t-1}$)	0.0001	-0.0019**	0.0024	-0.0001
95 % confidence interval	*-0.0016*	*-0.0035*	*-0.0008*	*-0.0007*
	0.0019	*-0.0003*	*0.0055*	*0.0005*
Constant	0.9468***	0.7766***	0.6738***	0.164**
sigma_u	0.1434	0.1277	0.1300	0.0159
sigma_e	0.0360	0.0383	0.0533	0.0141
rho	0.9406	0.9174	0.8561	0.5601

* Statistically significant at the 0.10 level
** Statistically significant at the 0.05 level
*** Statistically significant at the 0.01 level
Note: VA=Value Added, Dur=Durable Goods, NonDur=Nondurable Goods, Priv=Private Industry

Table 5C: Results of Analysis, Elasticities (No Local Variables)

	Manufacturing	Durable Goods	Nondurable Goods	Private Industry
2nd Quarter Indicator (*Q_2*)	0.009***	0.0091***	0.0092***	0.0012
3rd Quarter Indicator (*Q_3*)	0.0046**	0.0131***	-0.0035	0.0005
4th Quarter Indicator (*Q_4*)	0.0062***	0.0082***	0.0027	0.001
Manufacturing VA Lagged 1 Quarter (*$VA_{man,t-1}$*)	1.1164***			
Manufacturing VA Lagged 2 Quarters ($VA_{man,t-2}$)	-0.0501			
Manufacturing VA Lagged 3 Quarters (VAman,t-3)	-0.1747***			
Durable Goods VA Lagged 1 Quarter (VADur,t-1)		1.1414***		
Durable Goods VA Lagged 2 Quarters (VADur,t-2)		-0.0039		
Durable Goods VA Lagged 3 Quarters (VADur,t-3)		-0.3016***		
Durable Goods VA Lagged 4 Quarters (VADur,t-4)		0.0802***		
Nondurable Goods VA Lagged 1 Quarter (*$VA_{NonDur,t-1}$*)			1.0247***	
Nondurable Goods VA Lagged 2 Quarters ($VA_{NonDur,t-2}$)			0.0087	
Nondurable Goods VA Lagged 3 Quarters (VANonDur,t-3)			-0.1706***	
Nondurable Goods VA Lagged 4 Quarters (VANonDur,t-4)			0.0369	
Private Industry VA Lagged 1 Quarter (VAPriv,t-1)				1.0553***
Private Industry VA Lagged 2 Quarters (VAPriv,t-2)				0.013
Private Industry VA Lagged 3 Quarters (VAPriv,t-3)				-0.0787***
State Government Construction (GOVCNSTLoc,t-1	0.0021	-0.0007	0.0058	0.0001
Private Construction (PRIVCNSTLOC,t-1)	-0.0051	-0.005**	-0.002	-0.0031**
State Government Construction Supply Chain (GOVCNSTSCHN,t-1)	0.0001	0.0001	0.0009	<0.0001
Private Construction Supply Chain (PRIVCNSTSCHN,t-1)	0.0144***	0.0048	0.0189***	0.0007
Supply Chain Outage (SUPCHNt)	-0.0063***	-0.0040***	-0.009***	-0.0023***
95 % confidence interval	*-0.0077*	*0.0000*	*0.0000*	*0.0000*
	-0.0050	*-0.0066*	*-0.0107*	*-0.0030*
Constant	0.9704***	0.7665***	0.7371***	0.1516**
sigma_u	0.1437	0.1265	0.1315	0.0146
sigma_e	0.0355	0.0382	0.0527	0.0139
rho	0.9424	0.9164	0.8618	0.5236

* Statistically significant at the 0.10 level

** Statistically significant at the 0.05 level

*** Statistically significant at the 0.01 level

Note: VA=Value Added, Dur=Durable Goods, NonDur=Nondurable Goods, Priv=Private Industry

Table 6: Simulation of No Power Disturbances: Percent Change in Value added

	Manufacturing	Durable Goods	Nondurable Goods	Private Industry
Local Power Disturbance	-	-	-	-
Supply Chain Power Disturbance	2.3%	1.5%	3.3%	0.8%
95 % Confidence Interval	*-0.5%*	*-1.8%*	*-0.8%*	*-0.2%*
	5.2%	*4.7%*	*7.4%*	*1.8%*
Observations	2757	2756	2756	2764
R2	0.9991	0.9992	0.9980	0.9998

Table 7: Support for Hypothesis

	Dependent Variable (value added)			
	Manufacturing	Durable Goods	Nondurable Goods	Private Industry
1. Power Disturbances in the supply chain reduce manufacturing value added locally.	Yes			
2. Power Disturbances in the supply chain reduce durable goods value added locally.		Yes		
3. Power Disturbances in the supply chain reduce nondurable goods value added locally.			Yes	
4. Power Disturbances in the supply chain reduce private industry value added locally.				Yes

Table 8: Estimated U.S. Losses due to Power Outages

	Current Dollars (billion)		Constant 2016 Dollars (billion)	
	low	high	low	high
Swaminathan and Sen (1997)	150		224	
Primen (2001)	119	188	161	255
LaCommare and Eto (2006)	22	135	26	161
Campbell (2012) - weather related	20	55	21	57
President's Council of Economic Advisers et al. (2013)	18	33	19	34

Table 9: Potential Return on a $50 billion Investment in Energy Resilience

			Decrease in Losses from $50 B Investment	Present Value ($million)	Net Present Value ($million)	Internal Rate of Return	Payback Period (years)
Excluding Direct Impact	2 % Degradation	20 Year Study Period	No Investment	-1 658 720	NA	NA	NA
			25%	-1 367 878	290 842	63.1%	2
			20%	-1 436 046	222 674	50.0%	2
			15%	-1 504 215	154 505	36.9%	3
			10%	-1 572 383	86 337	23.6%	4
			5%	-1 640 552	18 168	9.4%	9
		10 Year Study Period	No Investment	-1 027 763	NA	NA	NA
			25%	-847 025	180 737	62.7%	2
			20%	-893 173	134 590	49.3%	2
			15%	-939 320	88 442	35.5%	3
			10%	-985 468	42 295	20.8%	4
			5%	-1 031 615	-3 853	3.3%	9
	5 % Degradation	20 Year Study Period	No Investment	-1 658 720	NA	NA	NA
			25%	-1 478 634	180 086	57.4%	2
			20%	-1 524 651	134 069	44.6%	3
			15%	-1 570 669	88 052	31.7%	3
			10%	-1 616 686	42 034	18.3%	5
			5%	-1 662 703	-3 983	3.6%	11
Including Direct Impact (Low estimate)	5 % Degradation	20 Year Study Period	No Investment	-1 895 502	NA	NA	NA
			25%	-1 682 572	212 931	66.5%	2
			20%	-1 735 158	160 345	51.9%	2
			15%	-1 787 744	107 758	37.2%	3
			10%	-1 840 330	55 172	22.2%	4
			5%	-1 892 916	2 586	5.9%	9
Including Direct Impact (High estimate)	5 % Degradation	20 Year Study Period	No Investment	-4 836 584	NA	NA	NA
			25%	-4 215 687	620 897	178.9%	1
			20%	-4 349 866	486 717	142.0%	1
			15%	-4 484 046	352 538	105.1%	1
			10%	-4 618 225	218 359	68.0%	2
			5%	-4 752 404	84 179	30.6%	3

Note: Green indicates it is an economical investment

Note: Red inicates that it is not economical