Estimating the economic cost of load shedding in South Africa

A report for Eskom Holdings (SOC) Ltd.

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The opinions expressed herein are those of the authors and do not necessarily represent the views of Eskom SOC Holdings or its employees.
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<th>Description</th>
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<tbody>
<tr>
<td>ARDL</td>
<td>Autoregressive distributed lag</td>
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<tr>
<td>CLRM</td>
<td>Classical linear regression model</td>
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<tr>
<td>CGE</td>
<td>Computable general equilibrium</td>
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<tr>
<td>CoLS</td>
<td>Cost of load shedding</td>
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<tr>
<td>CoUE</td>
<td>Cost of unserved energy</td>
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<tr>
<td>DCGE</td>
<td>Dynamic computable general equilibrium</td>
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<tr>
<td>FBM</td>
<td>Feeder balancing module</td>
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<tr>
<td>GE</td>
<td>General equilibrium</td>
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<tr>
<td>GW</td>
<td>Gigawatt</td>
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<td>GWh</td>
<td>Gigawatt hour</td>
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<td>GDP</td>
<td>Gross Domestic Product</td>
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<td>GFCF</td>
<td>Gross fixed capital formation</td>
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<td>GVA</td>
<td>Gross value add</td>
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<td>IPP</td>
<td>Independent power producer</td>
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<td>I-O</td>
<td>Input-output</td>
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<td>IoS</td>
<td>Interruption of supply</td>
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<td>kWh</td>
<td>Kilowatt-hour</td>
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<td>LFS</td>
<td>Labour force survey</td>
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<td>LSDV</td>
<td>Least-squares dummy variable</td>
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<td>MW</td>
<td>Megawatt</td>
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<tr>
<td>MWh</td>
<td>Megawatt-hour</td>
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<tr>
<td>NERSA</td>
<td>National Energy Regulator of South Africa</td>
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<tr>
<td>OVB</td>
<td>Omitted-variable bias</td>
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<tr>
<td>OCGT</td>
<td>Open cycle gas turbine</td>
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<tr>
<td>OLS</td>
<td>Ordinary least squares</td>
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<tr>
<td>PE</td>
<td>Partial equilibrium</td>
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<tr>
<td>PALMS</td>
<td>Post-Apartheid Labour Market Series</td>
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<td>QLFS</td>
<td>Quarterly labour force survey</td>
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<tr>
<td>q/q</td>
<td>Quarter-on-quarter</td>
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<tr>
<td>Rm</td>
<td>Rand million</td>
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<tr>
<td>SAM</td>
<td>Social accounting matrix</td>
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<tr>
<td>SARB</td>
<td>South African Reserve Bank</td>
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<tr>
<td>SIC</td>
<td>Standard industrial classification</td>
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<tr>
<td>StatsSA</td>
<td>Statistics South Africa</td>
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<tr>
<td>SNA</td>
<td>System of National Accounts</td>
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<tr>
<td>UCT</td>
<td>University of Cape Town</td>
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<td>VoLL</td>
<td>Value of lost load</td>
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Executive summary

In late 2007, South Africans experienced the first of what would become a recurring series of nationwide load shedding episodes. Load shedding refers to the deliberate shutdown of parts of the electricity distribution network to avoid damaging the electricity grid and to safeguard against a national blackout. It is usually implemented after alternative options to balance demand and supply have been exhausted. Load shedding is implemented to reduce electricity demand, preserve grid stability, and to prevent the collapse of the system.1

The first load shedding episode in October 2007, marked the beginning of a national electricity supply crisis that has persisted for over a decade. Weekly data from the Eskom’s system operator show that load shedding occurred during 33 months between 2007 and 2019. There have been three distinct periods of load shedding over the past 12 years – the first ran from 2007 to 2008, the second from 2013 to 2015, and the most recent from 2018 to late 2020. While load shedding has continued into 2020, we limited to our analysis to the 12 years ending in 2019.

Load shedding has caused significant disruption in the daily lives of South Africans and the national economy. The purpose of this study was to provide Eskom with reliable and accurate estimates of the economic cost of load shedding in South Africa.

We have estimated that Load shedding cost the South African economy nearly R35 billion in the 12 years between 2007 and 2019.2 Had all the load shedding experienced over the period taken place in a single quarter in 2019, it would have resulted in a 5% contraction real q/q GDP growth. To put this into perspective the total cost of load shedding at R35 billion is roughly equivalent to the impact the 2008/9 financial crisis had on GDP growth (it also subtracted a cumulative five percentage points from quarter-on-quarter GDP growth albeit over a much shorter period).

Our results suggest that the cost of load shedding (CoLS), expressed in rand per kilowatt-hour, increased over the three main periods in which it occurred. During the first period (2007 to 2008) the CoLS was R7.61/kWh, it rose to R8.80/kWh during the second period (2013 to 2015) to R9.53/kWh in the third period (2018 to 2019). Our results of the total CoLS are similar to Eskom’s previous estimate of R8.95/kWh, which was produced by Deloitte in 2009.5

Another objective of this study was to give Eskom insight into the distribution of the CoLS across different sectors of the economy. We were able to produce estimates of the CoLS for all sectors

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1 Also referred to as rolling blackouts
2 Expressed in 2020 prices.
3 Expressed in 2020 prices.
4 Expressed in 2020 prices.
Our results show that the CoLS is unevenly distributed – four of the nine industries, namely manufacturing (SIC 3), transport and communication (SIC 6), wholesale and retail trade (SIC 5) and agriculture, hunting, forestry and fishing (SIC 1), bore 80% of the total cost. The manufacturing sector alone, shouldered nearly 40% of the total cost.

We also normalised the CoLS to illustrate the impact of load shedding on each sector relative to its size (contribution to total GDP). For example, we saw that while the agricultural sector was the worst-affected, the manufacturing sector, which accounts for 13% of GDP carried the highest proportion of the total CoLS. While the agricultural industry is a relatively small contributor to national GDP (it accounts for 3.6% of total output) it lost 4.2 times more GDP per kWh of load shedding than the average. Manufacturing (SIC 3) and utilities (SIC 4) lost three times more output than the average. The output of the most service-oriented sectors was largely unaffected by load shedding – this included financial and business (SIC 7) and community, social and personal services industries (SIC 8).

The total cost of regular planned outages, as defined in the international literature, is a function of the damages and costs incurred by a firm, its inherent resilience and ability to adapt. A firm may incur costs related to direct and/or indirect damages (e.g. lost production or reduced productivity). The inherent resilience of a particular firm or industry refers to its ability to shift production around outages while the ability to adapt refers to the extent to which it can invest in alternative sources or back-up generation.

There are several reasons, for example, why one would expect service-oriented industries to be inherently more resilient to power outages and better able to adapt. By way of illustration, personnel in the finance and business services industry can continue to work during power outages if the electronic devices they rely on, such as laptops and IT systems, are fitted with back-up power generation sources. Working hours in this industry tend to be more flexible so that people can shift their working hours to better accommodate load shedding. Our estimate of the CoLS for the finance industry (if the total cost to the economy is normalised to R1/kWh) is just three cents per kWh.

Our estimates of the CoLS are based on an econometric analysis of the historical relationship between load shedding and GDP. Our estimates capture the CoLS, as reflected in the variation in GDP growth (q/q) around its long-term trend. This includes direct and indirect damages (e.g. loss of output) and the costs of adaptation and mitigation (e.g. higher costs such as investment in back-up generation).

These estimates, however, do not include the longer-term costs of load-shedding (e.g. related to reduced business and investor confidence). These longer-term costs would be reflected in a lower long-run trend GDP growth, but it is not possible to estimate what the trend in growth might have been if load shedding had not occurred. While many factors have contributed to the gradual decline

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6 A reliable estimate of the impact of load shedding on mining GDP could not be obtained as it was not possible to control for more than 10% of the variation in the highly volatile quarter-on-quarter growth in Mining GDP.
in South Africa’s trend GDP growth over the past decade, there is little doubt that load shedding and persistent electricity supply constraints were among them. From this perspective, our estimates of the CoLS can be considered somewhat conservative because they exclude the longer-term impact of recurring outages on business and investor confidence which cannot be easily identified with econometric techniques.

Finally, it was envisaged that the estimates of the CoLS could inform future energy-sector policy and strategic decision making. In particular, measures of the cost of outages are useful in assessing the relative costs of interventions to mitigate against the risk of future load shedding, and so can be used to make socially optimal investment decisions.

Eskom and its shareholder, the South African Government, face several choices when assessing how best to mitigate against the risk of further load shedding. There are several potential options to consider on both the demand and supply-side, but all these interventions are associated with financial and/or broader economic costs.

The immediate options are limited but on the supply-side, they would include running emergency generation or peaking plant (e.g. diesel-fired open cycle gas turbines) at higher load factors and on the demand-side power buybacks from customers already under contract, voluntary curtailment by top customers or as a last resort load shedding. There are more options in the short-to-medium term, including returning moth-balled power plants to service, building or procuring utility-scale renewable capacity, investing in large-scale energy-efficiency and demand-side management programmes or entering into new interruptible supply agreements.

The socially optimal choice is the one that minimises the net cost to society. It is also important, however, to consider who bears the costs. For example, if the system operator decides to run Eskom’s peaking plant (OCGTs) at higher load factors in a bid to avoid load shedding, Eskom bears the cost and must motivate to recover the costs from the consumer via a higher tariff.

While the cost of load shedding at R9.53/kWh is higher than the cost of running OCGTs estimated by EPRI at R1.99/kWh (2015 prices), it is borne mainly by the most energy-intensive sectors of the economy (e.g. manufacturing, mining, and transport, while Eskom itself only bears a small proportion the cost (i.e. lost electricity sales).
1. Background and context

1.1. Purpose of the study and key objectives

The purpose of this study was to provide Eskom with reliable and accurate estimates the economic cost of load shedding (CoLS) between 2007 to 2019. Eskom’s previous estimate of the CoLS was produced by Deloitte in 2009. The main objective of this study was to update Eskom’s 2009 estimate of the national CoLS. A further objective was to explore how the cost of load shedding differs and is distributed across different sectors of the economy.

It is envisaged that estimates of the CoLS will be useful in informing energy sector policy. Measures of the cost of outages are particularly useful in assessing the relative economic costs of interventions to mitigate the future risk of load shedding, to make socially optimal investment decisions.

Our estimates of the CoLS were produced using econometric analysis of the historical relationship between the magnitude and incidence of load shedding and GDP. Our estimates capture the CoLS, as reflected in the variation in GDP growth (q/q) around its long-term trend. This would include direct and indirect damages (e.g. loss of output) and the costs of adaptation and mitigation (e.g. higher costs such as investment in back-up generation).

These estimates of the CoLS, however, can still be considered conservative, because they exclude the longer-term impact of recurring outages on business and investor confidence which cannot be captured using econometric techniques. These longer-term costs would be reflected in a lower long-run trend GDP growth, but it is not possible to estimate what the trend in growth might have been if load shedding had not occurred. While many factors have contributed to the gradual decline in South Africa’s trend GDP growth over the past decade, there is little doubt that load shedding and persistent electricity supply constraints were among them.

1.2. What were the events that precipitated the power crisis in South Africa?

In October 2007, the lights went out as South Africa experienced the first in a series of nationwide load shedding episodes. Load shedding refers to the deliberate shutdown of parts of the electricity distribution network to avoid damaging the electricity grid and to safeguard against a national blackout.

When electricity demand exceeds the available supply, the electricity grid becomes unstable. This could cause generation units to trip, further compromising the system. A loss of generation capacity, in this context, increases the load on the remaining units and, in a worst-case scenario, a
cascading effect with multiple power station failures culminating in a national blackout. Such a collapse of the electricity grid would leave the country without electricity for several days.\(^7\)

To avoid this, a utility or system operator will implement load shedding when national electricity demand is threatening to exceed supply (when alternative interventions to increase supply in the short-term have been exhausted). Rotational load shedding is usually implemented in blocks of two to four hours – with various parts of the network affected at different times.

While several factors contributed to the emergence of South Africa’s electricity supply crisis in 2007, chief among them was the failure by government to implement the ambitious electricity sector reforms that had been outlined in the 1998 Energy Sector White Paper. The model of power-sector reform laid out in the White Paper recommended the vertical and horizontal unbundling of Eskom to separate the potentially competitive components of the industry (e.g. generation) from those that are natural monopoly (i.e. transmission and distribution). The main objectives of the policy paper included attracting private sector investment into the electricity generation sector, ensuring a transition to cost-reflective electricity prices, expanding basic access to electricity and consolidating the highly fragmented municipal distribution industry.

The South African Government, however, had not appreciated the extent to which Eskom’s highly subsidised electricity price, would deter the private sector from investing in the sector. The price of electricity had been implicitly subsidised by the government for over a decade and did not reflect the true cost of generating, transmitting and distributing power. There was therefore little financial incentive, for the private sector to invest.

At that stage, there was also no specific regulatory framework to facilitate the participation of independent power producers (IPPs). Ian McRae, a former CEO of Eskom, noted in 2009 that despite its intention to source power from IPPs since 1998, by 2009 it had failed to sign a single power purchase agreement: “The government failed to recognise that IPPs would not rush into South Africa to compete with Eskom’s large, low-cost, coal-fired stations”.

In 2004, Thulani Gcabashe, then CEO of Eskom, warned the parliamentary portfolio committee that available generation capacity was “reaching its limit”. As a result, the government was forced to reconsider the position adopted in 2001 that Eskom should be prohibited from building new generation capacity and, in 2004, gave Eskom the green light to embark on a five-year capacity expansion programme. The then Managing Director of Eskom Enterprises, Brian Dames, noted that this would begin with the restoration of mothballed plants to service and the installation of two new open-cycle gas turbines (OCGTs) to serve as peak generation capacity. He, however, noted that Eskom’s decision on the commissioning of new baseload capacity would be deferred until 2010.\(^8\)

In 2007, Eskom warned that the system would become constrained within the next five or six years. The utility and called for a collaborative effort from all stakeholders to minimise the likelihood of

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power interruptions. Shortly thereafter, in October 2007, Eskom implemented the first round of load shedding. Then-President Mbeki accepted responsibility for the oversight in planning. On the 12th of December 2007, he made a public apology, noting that “Eskom was right, the government was wrong.” As a result, in 2007 the Eskom board was able to fast-track the approval of a massive capacity expansion programme including the construction of two large coal-fired power stations - Medupi and Kusile.  

The failure by government and its regulatory authorities (over several decades) to transition to cost-reflective electricity tariffs also contributed to the emergence of the power crisis. By 2007, the real electricity price reached all-time lows. Eskom had neither the capital reserves nor the future revenue stream to cover the cost of the new build programme. This prompted the National Energy Regulator of South Africa (NERSA) to approve several sharp increases in annual tariffs. The regulatory methodology applied by NERSA allows Eskom to recover all its prudently and efficiently incurred costs including a return on capital invested in new generation assets. Between 2008 and 2013, electricity prices more than doubled in real terms (inflation-adjusted) rising by a cumulative 114%, while nominal prices rose by 191% over the same period.

The sharp increases in real electricity tariffs over this period provoked a public outcry, and NERSA subsequently decided to limit the increase in real electricity tariff to ~2% per year between 2013 and 2018. This was much lower than the increase that Eskom required to reach cost-reflective tariff (CPI plus ~10% per year). NERSA disallowed a substantial proportion (over R100 billion) of Eskom’s budgeted costs between 2013 and 2018. This limited Eskom’s ability to mitigate the risk of further load shedding, as there was limited funding for demand or supply-side initiatives.

A previous study, produced by researchers at the University of Cape Town, noted that the implementation of an unsustainable maintenance strategy of ‘keeping the lights on at all costs’ and poor coal planning, contracting and procurement also contributed to repeated load shedding. The study suggests that Eskom’s ability to respond to the crisis was also hampered by a substantial loss in skills and capabilities – the result of sector reform and transformation policies which encouraged early retirement of many of the utility’s most experienced staff.

1.3. When and how often did load shedding occur?

Eskom’s system operator provided us with weekly data on the incidence and magnitude of load shedding from 2007 to 2019. While load shedding continued into 2020, we limited to our analysis to the period between 2007 and 2019. This was firstly, because comparable economic data for 2020 had not yet been released and secondly because it would have been difficult to accurately isolate
the impact of load shedding from the tremendous economic shock precipitated by the COVID-19 pandemic during 2020.

Load shedding occurred in a total of 33 months between 2007 and 2019 (Figure 1). From the data illustrated in Figure 1, it is clear that between 2007 and 2019 load shedding occurred in three main periods:

- Period 1: October 2007 to April 2008 (load shedding during 7 of 7 months)
- Period 2: November 2013 to October 2015 (load shedding during 16 of 24 months)
- Period 3: June 2018 to September 2020. The 2020 incidents were excluded from the scope of our analysis – we focused on the period until the end of December 2019 where load shedding occurred during 9 of 19 months.

According to estimates provided by the system operator, the average monthly magnitude of load shedding was 122 GW. The single month in which the largest amount of load shedding occurred was March 2019 when an estimated 420 GWh of electricity demand could not be met. The most sustained period of load shedding was from 2013 to 2015 when load shedding occurred in 16 months.

Figure 1 Monthly data on the incidence of load shedding, 2007 until 2019

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<tr>
<td>872 GWh</td>
<td>1 742 GWh</td>
<td>1 307 GWh</td>
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Source: Nova Economics analysis, based on data supplied by the Eskom system operator
1.4. Why does load shedding occur? The reserve margin in the context of long-term electricity supply shortages

An electricity utility must continuously match the supply of electricity from its generation fleet with the load demanded by its customers. However, producing an accurate forecast of electricity demand, both in the short-term (i.e. day-ahead) and long-term, is a complicated task. To avoid underestimating electricity demand and to account for other unforeseen factors, electricity utilities operate at a slight oversupply. This surplus capacity is referred to as the reserve margin.

The utility’s system operator must balance the cost of surplus capacity with the risk of not meeting demand. The reserve margin also provides some leeway for irregular spikes in demand and unexpected failures in supply. Eskom’s targeted operating reserve margin is 15% (i.e. dispatchable electricity supply exceeds forecast peak demand by 15%), which is consistent with optimal levels in literature. In the literature, adequate reliability is defined as “the level of reserves that provide an expectation of less than one event in 10 years due to generation deficiency.”

A narrow reserve margin poses a substantial risk to the stability of the national grid as a result of a catastrophic cascading failure, while margins that are much above targeted optimal levels are inefficient. Regular planned outages occur when the reserve margin regularly drops below the target level over time. In this case, the margin does not provide an adequate buffer against unexpected electricity supply or demand side deviations. Once the reserve margin has been eroded, the system operator may be forced to implement load shedding.

The reserve margin depicted represents the surplus of capacity over demand during peak periods (Figure 2). While the initial period of load shedding came to an end in mid-2008, this was not because the underlying electricity supply shortage had been resolved but rather because of the negative impact of the 2008/9 global financial crisis on the SA economy (Figure 2). A sharp contraction in economic activity led to a parallel drop in electricity demand, and Eskom’s reserve margin increased to a comfortable 15 to 20%. However, with the recovery of the South African economy and international commodity markets in general, electricity demand increased. This economic recovery led to the gradual erosion of Eskom’s reserve margin, once again.

After the first period of load shedding, Eskom adopted a policy of ‘keeping the lights on’ which meant postponing scheduled maintenance to prevent load shedding at all costs. At roughly the same time, Eskom began to roll out an energy-efficiency and demand-side management programme on behalf of the Department of Energy.

By mid-2013, however, it was clear that Eskom could no longer afford to postpone maintenance because inadequate maintenance was adversely affecting plant reliability and the reserve margin had fallen to just 3%. Eskom was forced to reintroduced rotational load shedding, from 2013 to the

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12 Deloitte, “Modelling the impacts of electricity disruptions, Chapter 3, Report on Eskom and the Electricity Sector.”
14 Deloitte, “Modelling the impacts of electricity disruptions, Chapter 3, Report on Eskom and the Electricity Sector.”
end of 2015, to “create room” to resume scheduled maintenance. The period with the most sustained and significant load shedding was the final quarter of 2015. The reserve margin was restored to comfortable levels in 2016 and 2017 as new generation capacity including unit 5 of Medupi, Unit 1 of Kusile and Ingula pumped storage came online. A large proportion of new renewable IPP generation capacity was also commissioned (almost 5 000 MW).

In late 2018/19 Eskom reintroduced load shedding in the context of severe financial challenges. The National Energy Regulator of South Africa (NERSA) approved tariff increases that were far below what Eskom required in terms of the approved methodology, and this further jeopardised the utility’s financial sustainability as sales continued to stagnate. Eskom reported in its 2019 Integrated Report\[^{15}\] that it had faced severe operational challenges related to coal supply and quality issues, deteriorating generating plant performance due partly due to a lack of funds to carry out planned capital expenditure and maintenance. Eskom also faced uncertainty about restructuring and was in the process of addressing previously reported incidences of irregular spending and was in the process of restoring good governance.

Instituted policy of *keeping the lights on* & postponing planned maintenance. Also introduced demand-side management.

Eskom could no longer postpone maintenance, dealt a financial blow by inadequate tariff increase.

Slump in electricity demand due to the impact of 2008/9 global financial crisis.

Ingula, Medupi 5, Kusile 1 and IPP renewable plants commissioned. Plant availability increased due improved maintenance.


Source: Nova Economics analysis data provided by Eskom
2. Electricity supply interruptions – the key concepts

2.1. Introduction

In this section, we discuss some of the key concepts relevant to measuring the costs of electricity supply interruptions. These include the distinction between planned and unplanned outages, the measures that are typically used and the types of costs associated with outages.

2.2. Distinguishing between planned and unplanned supply interruptions

The literature on power outages distinguishes between two main types of interruptions - infrequent, unplanned outages and regular, planned outages (Table 1). Unplanned outages are defined as infrequent, of short duration (usually lasting less than three hours). Unplanned outages take place within even the most well-planned systems and often in the context of an adequate reserve margin. Because they are infrequent, most consumers do not anticipate them and do not invest in back-up supply or processes to mitigate against the risk of unplanned outages.

Planned outages by contrast, usually take place in the context of a persistent structural shortage of electricity capacity, and an inadequate operating reserve margin. Because the outages are planned, consumers have time to adapt. Consumers may adapt by investing in mitigating measures (e.g. backup generation and storage) or by employing resilience tactics (e.g. reducing reliance on electricity as a single source of energy or shifting production to avoid load shedding).

Table 1 The distinction between the two main types of electricity supply interruptions

<table>
<thead>
<tr>
<th>Unplanned outages</th>
<th>Electricity supply shortages</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Infrequent, unplanned occur suddenly</td>
<td>• Regular, planned and unplanned outages</td>
</tr>
<tr>
<td>• Usually &lt; 3 hours duration</td>
<td>• Typically scheduled, but sometimes sudden</td>
</tr>
<tr>
<td>• Electricity demand temporarily exceeds supply</td>
<td>• Due to a structural or long-term shortage of electricity capacity, usually low and middle-income countries (e.g. Zambia, Nigeria, South Africa, Pakistan)</td>
</tr>
<tr>
<td>• Stable reliable power supply, an adequate reserve margin</td>
<td>• Power system reserve margin is inadequate</td>
</tr>
<tr>
<td>• Very few customers have a back-up supply or invest in other mitigation measures</td>
<td>• Customers invest in back-up supply or other mitigation measures</td>
</tr>
<tr>
<td>• Occur in both developed and developing countries</td>
<td>• Also referred to as the cost of power shortages</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Cost of unserved energy (CoUE)*</th>
<th>Cost of load shedding (CoLS)**</th>
</tr>
</thead>
</table>

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18 We use the term consumers to collectively refer to the various types of electricity users, including households, businesses, government institutions, etc.
• The value (in rand per kWh) that is placed on a unit of energy not supplied due to an unplanned outage of short duration
• Also referred to as the Value of Lost Load (VoLL)
• Electricity system planners aim to balance the CoUE against the cost to supply the energy not serve
• In SA, a methodology was developed to estimate CoUE for use in transmission and distribution network planning (as required by the Distribution Network Code)

• The value (in rand per kWh) that is placed on a unit of electricity not delivered due to frequent, recurring, and planned outages
• Accounts for the inherent resilience and adaptive response of end-users (i.e. investing in mitigating measures or inherently more resilient e.g. due to ability to substitute)
• CoLS can be used to assess the relative costs of interventions to reduce the risk of power outages occurring in future

* Used synonymously in the electric industry and the literature with “Value of Customer Reliability,” “Value of Lost Load,” “Cost of unplanned or unexpected interruptions.”
**Referred to in the literature as the cost of planned outages

Most consumers do not anticipate unplanned outages and do not invest in back-up supply or processes to mitigate against the risk of unplanned outages. Planned outages, by contrast, usually take place in the context of a persistent structural shortage of electricity capacity, and an inadequate operating reserve margin. Because the outages are planned, consumers have time to adapt. Consumers may adapt by investing in mitigating measures (e.g. backup generation and storage) or by employing resilience tactics (e.g. reducing reliance on electricity as a single source of energy or shifting production to avoid load shedding).

2.3. What measures have been used to estimate the cost of outages in South Africa?

In South Africa, the cost of unserved energy (CoUE) is the measure used to provide an estimate of the cost of unplanned outages. In the international literature, it is referred to alternately as the CoUE or the value of lost load (VoLL). While there are many ways to estimate the CoUE, it is most simply approximated as the gross-value add (GVA) produced for every unit of electricity consumed (e.g. R/kWh). The CoUE, therefore, represents the electricity intensity of each type of economic activity or region. The total CoUE for South Africa was estimated at R77.30 GVA/kWh in 2013 while the estimate of the CoUE approved by NERSA for use in 2020 is R91.72 GVA/kWh.

Eskom’s previous estimate of the cost of planned outages (and specifically load shedding) was produced by Deloitte in 2009. The Deloitte report estimated the CoLS using a forward-looking dynamic computable general equilibrium (DCGE) model. The report modelled various scenarios for productivity decline due to load shedding (assuming that load shedding renders capital stock idle) i.e. 10%, 5% and 2% decline, as well as a ‘realistic’ load shedding scenario where different sectors...
were affected to varying degrees. Their estimate of the CoLS, based on a simulation of a realistic load shedding scenario, was R4.92/kWh in 2008 values which equates to R8.95/kWh in 2020 values.

As would be expected, previous estimates of the CoLS in South Africa are much lower than the CoUE, because the cost of regular, planned outages takes into account the ability of consumers to adapt, to substitute the factors of production, to invest in a back-up generation or to work around the outages and limit losses in output. Methodologies to estimate the CoLS also typically take into account the inherent resilience of some industries – for example, employees at a professional services firm may be able to continue working when the power goes off or to simply shift their work to a time later in the day.

2.3.1. What can the CoUE and CoLS measures be used for?

According to De Nooij et al\textsuperscript{23} CoUE measures are used internationally to make socially optimal investment decisions and to determine which customers should be cut off in times of electricity supply shortages. Internationally, the CoUE is often used to assess whether investments in transmission and distribution networks are feasible or socially optimal. The CoUE has, however, also been used in tariff design and generation planning in some countries (Table 2).

Minaar, Visser and Crafford\textsuperscript{24} note that in the South African context the CoUE values are used exclusively to inform socially optimal investment decisions for utility systems. Both the South African Transmission Grid Code and the Distribution Network Code require the regulator – the National Energy Regulator of South Africa (NERSA) – to approve a method of determining the CoUE as an economic parameter for network investment criteria. The CoUE is also used in generation planning in South Africa where it has been used as an input to the Integrated Resource Plan to quantify the risk of economic damage (at macro-economic level) as a result of generation capacity inadequacy.

The CoUE is a proxy for the cost of unplanned, infrequent outages of short duration and is, therefore, best used when weighing up the relative costs and benefits of interventions to reduce unplanned outages or designing tariffs to compensate users for these interruptions, such as interruptible service charges.

The CoLS can be used when assessing the costs and benefits or initiatives to reduce the likelihood of load shedding, i.e. regular, planned outages. These include strategic decisions about whether to employ emergency capacity to avoid load shedding, such as peaking plants. The CoLS can also be used as an input to generation planning, to assess the relative costs of outages compared to investments in new generation capacity or demand-side management initiatives, tariff design, or compensation for voluntary curtailment (Table 2).


Table 2 Potential applications of measures of planned and unplanned outages

<table>
<thead>
<tr>
<th>Category</th>
<th>Applications</th>
<th>Measure</th>
</tr>
</thead>
</table>
| Generation planning             | • Optimising the reserve margin  
• Investment allocation criteria  
• Cogeneration and IPP planning  
• Return to service plant  
• OCGT/peaking station usage planning | CoLS or CoUE |
| Transmission & distribution     | • The economic justification for design requirements and  
investment spending and extension of the transmission  
and distribution network. | CoUE     |
| Operations & maintenance        | • Generation plant service scheduling  
• Inventory management (coal stockpiling)  
• Planned load shedding scheduling  
• Emergency load shedding  
• Service restoration sequence planning after outages | CoLS or CoUE |
| Tariff design                   | • Time of use tariff pricing design  
• Design of curtailable and interruptible tariffs | CoUE or CoLS |
| Demand management and energy efficiency strategy | • Assessing the relative costs of various measures to improve  
energy-efficiency – e.g. tariff design, demand-side management programmes. | CoLS |

Source: Nova Economics analysis adapted from Munasinghe and Sanghui (1988).

2.4. The costs associated with power outages

Consumers can be affected by outages both directly and indirectly. The overall impact differs based on factors, such as the context, timing, duration, and frequency of the interruptions and consumers’ reliance on electricity (Table 3). Electricity consumers incur direct costs an outage directly impacts activities and processes.  

The most prevalent direct cost to businesses, for example, is lost production and the accompanying opportunity cost of idle resources. Businesses may also incur additional shutdown and restart costs because of outages or interrupted electricity supply could cause equipment failure, inventory damage or spoilage, data loss or corruption, etc.  

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26 Munasinghe and Sanghui, “Reliability of Electricity Supply, Outage Cost and Value of Service: An Overview.”

27 de Nooij, Koopmans, and Bijvoet, “The value of supply security - the costs of power interruptions: Economic input for damage reduction and investment in networks.”
Indirect costs are incurred as the initial impact of an outage permeates through the value chain (e.g. delayed delivery of input materials, services, or products). For example, the shutdown of Factory A may reduce its supplies to businesses B and C, which in turn may be forced to reduce their production due to unavailability of necessary inputs.28

Indirect costs also include the lagged impacts of an outage, or series of outages on the economy, due to a loss of business confidence and investor sentiment over the long-term (Table 3). Our estimates of the CoLS include direct and indirect costs incurred over the short-to-medium term. Our estimates do not include the longer-term indirect cost to economic growth due to a loss of investor confidence. These longer-term costs would decrease the long-run trend GDP growth, but it is not possible to estimate what the trend in growth might have been if load shedding had not occurred. The persistent electricity supply constraints and load shedding are among a host of factors have contributed to the gradual decline in South Africa’s GDP growth over the past decade.

In the context of a persistent electricity supply shortage, consumers may experience a series of recurring outages. In these circumstances, consumers are more likely to employ measures or tactics to reduce the impact of outages. These measures are usually associated with costs, but consumers are willing to bear the costs if the future stream of benefits will outweigh the cost – i.e. if a business invests in a diesel generator, they expect the benefit of having a backup electricity supply to offset the capital and operating costs of the generator.

Table 3 Factors that impact the cost of electricity outages

<table>
<thead>
<tr>
<th>Damages and costs</th>
<th>Short-to-medium term</th>
<th>Longer-term costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct costs</td>
<td>Indirect costs</td>
<td>Indirect costs</td>
</tr>
<tr>
<td>• Lost production</td>
<td>• Cost to customers or impacted firms (e.g. delayed delivery of inputs, services, or final goods)</td>
<td>• Negative impact on consumer, business, and investor sentiment.</td>
</tr>
<tr>
<td>• Opportunity cost of idle resources</td>
<td>• Cost to suppliers of impacted firms (e.g. delayed orders or purchases of inputs)</td>
<td>• Loss of domestic and foreign investment over the medium- to long-term</td>
</tr>
<tr>
<td>• Shutdown and restart costs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Spoilage and damages</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Inconvenience, nuisance, and stress</td>
<td></td>
<td></td>
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<tr>
<td>• Lost leisure</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indirect costs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Negative impact on consumer, business, and investor sentiment.</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resilience measures and tactics</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Inherent</th>
<th>Adaptive</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Energy conservation and efficiency of operations</td>
<td>• Temporarily adopting alternative processes</td>
</tr>
<tr>
<td>• Ability to spread production over multiple facilities</td>
<td>• Substituting inputs</td>
</tr>
<tr>
<td>• Recapturing lost production at a later stage</td>
<td>• Shifting production to unaffected facilities</td>
</tr>
<tr>
<td>• Fail-safe equipment that allows proper shutdown procedures to take place</td>
<td>• Recapturing lost production once the electricity supply is restored</td>
</tr>
<tr>
<td></td>
<td>• Back-up generation and storage</td>
</tr>
</tbody>
</table>


28 Kingsley Oladipo Akpeji, “Cost of Electricity Interruption to Commercial and Industrial End-Users” (Master of Science in Electrical Engineering University of Cape Town, 2019).
Rose et al.\textsuperscript{29} distinguish between two different kinds of resilience – inherent and adaptive (Table 3). They note that inherent resilience can be defined as the “ability under normal circumstances (e.g., the ability of individual firms to substitute other inputs for those curtailed by an external shock [such as power outage], or the ability of markets to reallocate resources in response to price signals.”

A firm that is inherently resilient to power outages may perform processes or activities that are not reliant on electricity, it may having the ability to switch to alternative fuel sources or for example to shift production without affecting overall output.\textsuperscript{30} Adaptive resilience is defined as the ability to reduce the impact of outages due to ingenuity or extra effort (e.g., increasing input substitution possibilities in individual business operations. A firm, for example, may temporarily adopt alternative processes, substitute inputs, shift production to unaffected facilities, or recapture lost production once electricity supply is restored.\textsuperscript{31, 32}

\begin{itemize}
\item \textsuperscript{29} Rose, Liao, and Oladosu, “Business Interruption Impacts of a Terrorist Attach on the Electric Power System of Los Angeles: Customer Resilience to a Total Blackout.”
\item \textsuperscript{31} Rose, Liao, and Oladosu, “Business Interruption Impacts of a Terrorist Attach on the Electric Power System of Los Angeles: Customer Resilience to a Total Blackout.”
\item \textsuperscript{32} Munasinghe and Sanghui, “Reliability of Electricity Supply, Outage Cost and Value of Service: An Overview.”
\end{itemize}
3. Estimating the magnitude of load shedding

3.1. Introduction

The first step in estimating the cost of load shedding on the South African economy was to collect reliable data on the frequency and magnitude of load shedding.

Eskom has kept a detailed daily record of the date, time, and duration of load shedding events – at both a national and at a substation level. Since the national power crisis emerged in 2007, there have been three distinct periods of load shedding – October 2007 to April 2008, November 2013 to October 2015, and June 2018 to September 2020 (Figure 3).

While Eskom keeps a detailed record of when load shedding occurred, it is not possible to directly observe how much electricity would have been consumed in the absence of outages. As a result, while the frequency of load shedding is observable, the ‘magnitude of load shedding’ can only be estimated.

![Figure 3 Load shedding incidences by quarter, 2007-2020](image)

3.2. Two approaches to estimating the magnitude of load shedding

We have compared two estimates of the magnitude of load shedding. The first estimate was provided by Eskom’s system operator (the “top-down estimate”) and was derived by taking the difference between their national day-ahead forecast of electricity demand over 24 hours and actual demand during the hours when load shedding occurred (Table 4).

We derived the second estimate (the “bottom-up estimate”) from data on the incidence and duration of load shedding events by substation, and from data on curtailment by Eskom’s top customers. We provide a brief explanation of the approach taken to deriving these estimates in Section 3.2.1 and 3.2.2. The key differences between the two estimates are summarised in Table 4.
Table 4 Key differences in approach and data sources

<table>
<thead>
<tr>
<th>Data sources</th>
<th>Top-down estimate</th>
<th>Bottom-up estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data sources</td>
<td>Eskom System-operator Weekly data provided by the system operator on the frequency and their estimates of the magnitude of load shedding.</td>
<td>Distribution division • Monthly electricity sales by substation • Incidences of load shedding by substation Eskom top-customer division • Hourly sales to top customers • Incidences of load curtailment by top customers System operator • Monthly data on Eskom power buybacks from top customers</td>
</tr>
<tr>
<td>Summary of approach to estimating LS</td>
<td>The system operator estimated the magnitude of load shedding by calculating the difference between its one day-ahead forecasts of the national demand profile (without load shedding) and actual demand during load shedding.</td>
<td>• We derived the bottom-up estimate of loading by aggregating monthly data on the incidence &amp; duration of load shedding events by substation. • We derived the magnitude of load lost during each episode using monthly average electricity sales by substation. • We then added data on curtailment and power buybacks by Eskom’s top customers, based on data containing incidences of curtailments to top customers and detailed electricity sales data to these customers.</td>
</tr>
</tbody>
</table>

Source: Nova Economics analysis based on Eskom sales data

3.2.1. Top-down estimate of load shedding by Eskom’s system operator

The Eskom system operator produces an estimate of the magnitude of load shedding by taking the difference between its daily forecasts of the national electricity demand profile (by hour) and actual electricity demand during the hours when load shedding occurred. The system operators’ top-down estimate of load reduction is calculated as the difference between its forecast of national residual demand and the actual demand on the days when load shedding took place. It is also adjusted for the slight forecast error observed before and after load shedding took place.33 Further detail on the system operator’s approach to estimating the magnitude of load shedding is provided in Appendix A.

3.2.2. Bottom-up estimate of load shedding

We derived a second estimate (the “bottom-up estimate”) from data on the incidence and duration of load shedding events by substation, and from data on curtailment by Eskom’s top customers.

33 Residual demand is defined by the Eskom system operator as “The portion of the demand that is supplied by dispatchable resources”. This includes power sent out by Eskom onto the transmission (Tx) network; international imports; generation from dispatchable independent power producers (IPPs); and interruption of supply (IoS). IoS in turn refers to all contracted and mandatory demand reductions to maintain system frequency and security of supply including power buybacks and curtailment. It excludes demand contracted from IPPs.
The bottom-up estimate is based on data drawn from two separate sources:

- Data on curtailment by Eskom’s top customers[^34] (largest mining and industrial customers) supplied by Eskom’s top customer division within distribution. This includes:
  - Sales to top customers (in kWh) on an hourly basis from 2014 to 2019.
  - Curtailment by top customers (including date, start time and end time of all curtailment incidents).
  - Total power buybacks (in kWh) from top customers for the months during which load shedding occurred. This data was supplied by the system operator.

- Data on monthly electricity sales and the incidence and duration of load shedding supplied by Eskom’s distribution division.[^35]
  - Data indicating the duration (in minutes) and time (specified to the minute) of electricity supply interruptions (i.e. not exclusively load shedding, but all types of interruptions) across between 2007 – 2019 by overhead line.
  - Monthly electricity sales data indicating average monthly sales data on by substation from the Feeder Balancing Module (FBM) between 2012 -2019. There were 1,363 substations in this dataset.

For Eskom’s regular customers (excl. top customers), we obtained data on the monthly incidence and duration of electricity supply interruptions[^36] at an overhead line level. We also obtained a dataset which contained monthly electricity sales for each of Eskom’s 1,363 substations. Based on the sales data, we calculated the average amount of electricity sold via each substation in the absence of load shedding. After matching the overhead lines to substations, we estimated the magnitude of load lost per substation by multiplying the duration of interruptions (at an overhead line level) by the average electricity sales, at a substation level, for each month when load shedding was experienced. This allowed us to derive the magnitude of load shedding for all Eskom’s regular customers.

We then separately estimated the magnitude of load reduction by Eskom’s top customers who have either entered power buyback agreements or are subject to voluntary load curtailment. We followed a similar approach to that used for regular customers and estimated the magnitude of

[^34]: Eskom defines top customers as customers who consume more than 100 GWh per annum. Given the energy intensive nature of these customers’ operations, top customers often enter into electricity supply agreements with Eskom which specify that top customers are not subject to regular load shedding, but rather electricity curtailments or power buybacks.

[^35]: We understand that a single substation may be supplied by multiple transmission lines.

[^36]: This dataset contained all incidences of power interruptions, which includes incidences of load shedding as well as other supply interruptions, such as interruptions due to maintenance or cable theft, for example. We found that other supply interruptions, in minutes, comprised less than 0.3% of the total duration of interruptions. Due to the trivial contribution of other supply interruptions to total supply interruptions, we did not adjust the dataset to exclude these other interruptions.
curtailment by comparing sales on ‘an ordinary day’ for each day, month, and year to a very similar
day when curtailment had occurred (e.g. A typical Sunday or Monday in December 2015).

We used two data sets to estimate curtailment by top customers - the first was detailed hourly sales
data for top customers and the second was the incidence of curtailment including the date, start
and end times of each incident. Top customers who entered power buyback agreements with
Eskom are exempt from voluntary curtailment under stage 1 and 2 load shedding. So to complete
our bottom-up estimate of load shedding we added the magnitude of power buybacks from top
customers to the bottom-up estimate of curtailment on the on days where load shedding occurred
(Figure 4).

The composition of the bottom-up estimate of load shedding is presented in Figure 4. This
breakdown reveals that Eskom’s top customers (which account for approximately 40% of total
electricity consumption) contributed about 10% of the total national load reduction during periods
of load shedding. Eskom’s regular customers (which account for the remaining 60% of
consumption) carried a higher proportion of the total burden of load shedding (about 90% of total
load reduction).
Figure 4 Composition of the bottom-up estimate of load shedding

<table>
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<tbody>
<tr>
<td>Buybacks</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Curtailment</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
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</tr>
<tr>
<td>Bottom-up estimate</td>
<td>27</td>
<td>17</td>
<td>51</td>
<td>351</td>
<td>18</td>
<td>45</td>
<td>296</td>
<td>0</td>
<td>0</td>
<td>27</td>
<td>7</td>
<td>85</td>
</tr>
</tbody>
</table>

Source: Nova Economics analysis
3.3. Comparison of the two estimates of load shedding

The two approaches to estimating the magnitude of load shedding yielded very similar results, both in terms of magnitude and distribution of the incidents over time (Figure 5). The fact that there is very little difference between the top-down and our bottom-up estimates gives us confidence in the accuracy of the load shedding series. On aggregate, the two estimates differ by just one per cent over the assessment period.

The series shows that load shedding occurred in a total of 33 months between 2007 and 2019. The most severe period was from 2013 to 2015 when load shedding occurred in 16 months. The most severe month of load shedding was in March 2019, when our estimates suggest that between 420 GWh and 435 GWh of electricity demand could not be met.

It was initially our intention to use both load shedding estimates in our analysis to produce a range of costs. However, when we compared the explanatory power of each estimate in our regression analysis, we found the difference in the estimated parameters was negligible. As such, we have based our analysis of the economic costs of load shedding on the top-down, system operator’s estimate alone. The top-down estimate is easier to derive and Eskom’s system operator calculates it regularly for various applications.
Figure 5 Comparison of the two estimates of the magnitude of load shedding

Source: Nova Economics analysis based on data provided by Eskom
3.4. **Load shedding as a percentage of total electricity sales**

Load shedding has caused significant disruption in the daily lives of South Africans and as such, we were surprised to find that load shedding constituted a relatively small proportion of total electricity sales (Figure 6). The estimates of the magnitude of load shedding never exceeded two per cent of the total electricity consumed in any of the 52 quarters between 2007 and 2019. This implies that Eskom was able to meet an average of 98.4% of total electricity demand during every quarter when load shedding occurred.

![Figure 6 Load shedding as a percentage of sales, quarterly](image)

We also calculated the proportion of load shedding to total electricity sales every month; we found that load shedding did not exceed three per cent of total electricity demanded in any of the 33 months in which load shedding occurred (Figure 7).

![Figure 7 Load shedding as a percentage of sales, monthly](image)
4. Methods used to estimate the cost of load shedding

4.1. Broad analytical approaches that can be taken to estimating the cost of load shedding

The international literature on the cost of regular, planned outages is limited. Most of the economic literature on electricity supply interruptions focuses on partial equilibrium (PE) analysis of the cost of unplanned outages (CoUE). Wing and Rose note that, apart from a few case studies of actual events, the economy-wide losses that result from regular, planned load shedding (or even to some extent unplanned outages) were not typically analysed until the 1990s. We did, however, identify 13 studies that had to some extent explored the economic costs of regular, planned outages. A summary of the studies reviewed is provided in Appendix B.

Based on a review of this literature we noted that studies that estimate the cost of planned outages will typically follow one of two broad analytical approaches which we have categorised as forward-looking or retrospective (Figure 8).

4.1.1. Forward-looking approach to estimating the cost of planned outages

Studies that adopt a forward-looking approach will typically simulate the potential impact of load shedding on the economy under various hypothetical scenarios. The scenarios are usually simulated using a class of empirical economic models known as computable general equilibrium (CGE) models. CGE models fit economic data describing the microeconomic structure of an economy to a set of non-linear simultaneous equations that describe the theoretical interaction between firms, households, government, and the rest of the world.

The potential impact of load shedding on a specific sector or the national economy as a whole can be simulated using a CGE by constructing and applying a shock – e.g. by simulating a once-off 10% reduction in electricity supply – which in practice can be applied either by reducing the output of the electricity sector directly or by rendering a portion of each industry’s capital stock idle.

4.1.2. Retrospective approach to estimating the cost of planned outages

Studies that follow a ‘retrospective’ approach, aim to ascertain the impact that load shedding has historically had on economic growth in a particular sector, region, country, or group of countries. These studies employ various methods to try and ascertain the impact that regular planned outages have had on economic output during a particular event or series of events.

The retrospective studies were based on one of three methods – case studies of a particular event, revealed preference surveys or the statistical/econometric analysis of historic data on outages. Econometric models are statistical models that allow for the empirical verification of economic

theory or hypotheses. For example, examining whether the load shedding events have had a negative impact on GDP growth when controlling for the influence of other factors. We have provided a brief overview of what an econometric study entails in ‘Box 1. What is econometrics?’

**Figure 8 Analytical approaches and empirical methods used to estimate the cost of load shedding**

**Analytical approaches to estimating the CoLS**

**Forward-looking**
- Typically simulate the potential impact of load shedding under hypothetical scenarios.
- Some studies simulate adaptive responses including mitigation (e.g. back-up generator) & inherent resilience (e.g. delaying processes or finding substitutes).

**Retrospective**
- Aim to ascertain the impact load shedding has historically had on economic growth in a particular sector, region, country or group of countries.
- Attempt to isolate the marginal contribution of load shedding to the decline in economic output during a particular event or series of events.

**Empirical methods used**
- Scenarios typically generated using a class of empirical economic models know as computable general equilibrium (CGE) models. CGE models fit economic data describing the microeconomic structure of an economy to a set of non-linear simultaneous equations that describe the theoretical interaction between firms, households, government and the rest of the world.
- The potential impact of load shedding on a sector or national/regional economy can be simulated using a CGE by constructing and applying a shock – e.g. by simulating a one-off 10% reduction in electricity supply – either by reducing the output of the electricity sector directly or making 10% of capital stock idle.

**Empirical methods used**
- Retrospective studies are based on one of three methods – case studies of a particular event, data collected in revealed preference surveys or statistical/econometric analysis of historical data on outages.
- Econometric models are statistical models that allow for the empirical verification of economic theory or hypotheses – for example testing whether load shedding events have had negative impact on GDP growth. Some of the econometric techniques that have been used in previous studies to isolate the impact of load shedding on economic growth classical linear regression analysis, distributed-lag models, panel data regression analysis and vector auto-regression.

Source: Nova Economics analysis
Box 1. What is econometrics?

Econometrics is the study concerned with the empirical verification of the economic theory. Econometrics involves the application of a range of statistical techniques to economic data to empirically verify a hypothesis – for example, to test the extent to which load shedding had a negative impact on GDP growth.

In general, an econometric study will proceed along the following lines.

1. Statement of theory or hypothesis – e.g. load shedding subtracted from GDP growth.
2. Specification of the mathematical model of the theory – e.g. GDP can be expressed in terms of an energy augmented Cobb-Douglas production function:

   \[ Y_{it} = A_{it}K_{it}^\alpha L_{it}^\beta E_{it}^\gamma + \varepsilon_{it} \]

3. Specification of the statistical/econometric model – while mathematical models assume an exact or deterministic relationship between the variables and an econometric or statistical model allows for an inexact relationship between variables and always includes an error term or residual \( \varepsilon_t \). The econometrician also transforms variables so that the parameters can be estimated with the chosen statistical technique. For example, we take the natural logarithm in the above production function equation so that we can estimate the equation using the most well-used statistical estimation method – the classic linear regression model:

   \[ \ln(Y_{it}) = A_{it} + \alpha \ln(K_{it}) + \beta \ln(L_{it}) + \gamma \ln(E_{it}) + \varepsilon_{it} \]

   A simple two-variable linear regression between q/q GDP growth and load shedding as % of sales is depicted in the scatterplot, which serves as a visual depiction of a simple linear regression model, below. The line is fitted using an estimation procedure like OLS, which fits the line by minimising the squared residuals \( \varepsilon_t \).

4. Sourcing the data.

5. Estimation of the parameters – the statistical technique of regression analysis is the main tool used to estimate the parameters. The model suggests that load shedding is negatively correlated with GDP but that on its own, it only explains 23% of the variation, which means that we should include other determinants of GDP growth in our model to improve the fit and explanatory power of the model.

6. Hypothesis testing – run tests to see if the estimated parameter on load shedding (-0.7) is statistically different from zero (i.e. load shedding does not influence GDP), with the t-test, f-test, etc.

7. Application of the model and estimated parameters for insight, forecasting, or policy analysis.
4.2. Previous estimates of the cost of load shedding in South Africa

We identified three previous studies that had attempted to estimate the broader costs of load shedding in South Africa: Deloitte, 38 Goldberg 39 and Andersen and Dalgaard (Appendix B, App Table 1). 40 The first two studies focused on South Africa while the latter (Andersen and Dalgaard) assessed the impact of electricity shortages across 39 Sub-Saharan African countries, including South Africa.

In 2009, Eskom commissioned Deloitte to model the economic cost and impacts of the regular planned outages that occurred in 2007/8. This is one of the few studies that has attempted to measure the cost of load shedding, rather than estimating the cost of infrequent, unplanned outages (the CoUE) in South Africa. The key finding of the study was that load shedding was estimated, under the most realistic scenarios, to cost the economy R4.90/kWh in 2008 prices which would equate to ~R8.95/kWh in 2020 prices. This is much lower than the estimate produced that year of the CoUE infrequent unplanned outages of R75/kWh (PB Power, 2008).

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38 Deloitte, “Modelling the impacts of electricity disruptions, Chapter 3, Report on Eskom and the Electricity Sector.”
The Deloitte study adopted a forward-looking approach, the cost of load shedding was simulated using a dynamic computable general equilibrium model (DCGE). The authors considered three different scenarios to model the potential impact of load shedding. In the most realistic scenario, they cut the capital stock of each of the 40 sectors of the varying amounts (2%, 5% or 10%) based on the electricity intensity of the sector. This was based on the hypothesis that more electricity-intensive sectors are likely to have more equipment or capital stock rendered idle during a load shedding event with less ability to adapt or find alternatives.

A limitation of the study is that they simply assume that the load shedding event was equivalent to a load reduction of 3 000 MW and that this would result in a decline of between 2% and 10% in the capital stock of various sectors. This assumption was untested and was not calibrated to an actual historical incident or incidents.

Goldberg also attempted to estimate the cost of load shedding in South Africa, but the study was limited to assessing the impact on a sample of retailers in Gauteng. The study was based on semi-structured interviews with retail managers and stated-preference and revealed-preference survey techniques. The surveys made use of online and in-store questionnaires to capture stated preference or willingness of retail outlets to pay to avoid load shedding. The revealed preference techniques were used on actual financial information that was collected from retail head offices on the cost of providing back-up generation. These three methods enabled the author to derive different estimates on the cost of load shedding for retailers for different times of the day based on a customer damage function approach.

The biggest limitation of this study is the small sample size. The semi-structured interview insights were based on a sample of only eight interviews, while the sample sizes for the state-preference and revealed-preference methods were also limited (106 and 42 surveys respectively).

Andersen and Dalgaard follow a retrospective econometric approach to estimating the cost of power outages across 39 Sub-Saharan African countries including South Africa. The authors estimate the total effect of power outages on economic growth in Sub-Saharan Africa over the period 1995-2007.

41 Goldberg, "The economic impact of load shedding: The case of South African retailers".
While the authors attempt to pay close attention both to potential errors of measurement of African economic growth and to the endogeneity of outages, the study suffers from some limitations. Firstly, it makes use of a very parsimonious model of outages on economic growth – the authors explain economic growth only in terms of the GDP growth per capita, an intercept, the log of outages and an error term. In trying to limit the risk of multicollinearity and endogeneity, their model is likely to suffer from omitted variable bias. As a result, too much of the reported variation in GDP per capita was likely attributed to outages.

4.3. Previous econometric studies of the cost of load shedding

Some of the specific econometric techniques that have been used in previous studies to isolate the impact of load shedding on economic growth are classical linear regression analysis, autoregressive distributed lag (ARDL) models, panel data regression analysis and vector auto-regression (VAR) models.

Of the 13 studies we reviewed, four were based on an econometric analysis of the cost of historical electricity supply shortages. Fisher-Vanden, Mansur, and Wang,\textsuperscript{42} and Allcott et al.\textsuperscript{43} estimated the impact of electricity shortages based on panel data for manufacturing firms in China and India, respectively. Andersen and Dalgaard,\textsuperscript{44} as discussed earlier, estimated the impact of electricity shortages on GDP per capita across Sub-Saharan Africa using time series techniques, while Ellahi\textsuperscript{45} estimated the impact of electricity supply constraints on the development of the industrial sector in Pakistan using an ARDL model. A more comprehensive review and summary of the results, advantages and limitation of these studies can be found in Appendix B, Section B.3.

One of the main advantages of studies based on econometric analysis of historical time series or panel data is that, in contrast to highly stylised and theoretical GE models, the results are based on the empirical analysis of real-world outage events. Studies based on econometric analysis typically aim to isolate the impact of a particular load shedding event (or series of events) on economic growth or industry-level production. In this sense, they can be used to produce estimates of the actual historical economic costs (direct and indirect and net of adaptive response) of regular or persistent power shortages. For example, Andersen and Dalggaard\textsuperscript{46} estimated across a sample of 39 Sub-Saharan African countries that a one per cent increase in the number of outages reduced long-run GDP per capita by 2.86 per cent during the period 1997 to 2007.

\textsuperscript{44} Andersen and Dalgaard, “Power outages and economic growth in Africa.”
\textsuperscript{46} Andersen and Dalgaard, “Power outages and economic growth in Africa.”
Another advantage of retrospective econometric studies it that is possible to estimate the net impact of power shortages on different groups or sectors – to understand which firms or sectors are more resilient (able to avoid or cushion the impact) than others. For example, Allcott et al. found that in 2005 when Indian manufacturing firms faced outages, 7.1% of the time, that the output of firms that were able to self-generate (i.e. had back-up generators) lost only 0.7% of their output. Firms that did not have back-up generation lost 10.3% of their output. The authors concluded that electricity shortages were a substantial drag on Indian manufacturing from 1992 to 2010, reducing manufacturing output by an average of about five per cent over the period.

4.4. Our approach to estimating the CoLS

We estimated the historical impact of load shedding on GDP growth from 2007-2019. We have produced three alternative sets of estimates of the CoLS, based on three different econometric techniques – a classical linear regression, an auto-regressive distributed lag model and a panel data regression. The first two estimates are based on an expenditure-side model of the determinants of GDP while the third was based on an energy-augmented Cobb-Douglas production function (Figure 10).

Figure 10 Approach to estimating CoLS

1. Expenditure-side model of GDP
   - The expenditure-side models of the determinants of GDP are based on the national income identity where GDP (Y) is function of consumption expenditure (C) by firms and households, government spending (G), investment (I), plus exports (X) less imports (M).

2. Energy-augmented production function
   - We also estimated the impact of load shedding on GDP using a Cobb-Douglas production function. In terms of this standard theory of economic production, industries combine inputs including capital (K), labour (L) and Hicks-neutral technology (A) to produce output (Y) or gross value-added (GVA).

1a. Linear Regression
   - We produced the first set of estimates of the CoLS using a classical linear regression to estimate the expenditure-side model of GDP.

1b. ARDL
   - For the second set of estimates of the CoLS based on the expenditure-side model of GDP we use an Auto-regressive distributed-lag technique.

2a. A Panel data regression, OLS with fixed effects
   - We produced the third and final set of estimates of the CoLS by estimating the energy-augmented Cobb-Douglas production function in logarithmic form. We estimate the parameters as a system of equations using a panel regression technique known as the Fixed Effect Least-Squares Dummy Variable (LSDV) Model.

Allcott, Collard-Wexler, and O’Connell, “How do electricity shortages affect industry? Evidence from India.”
4.5. Estimation of the CoLS based on the expenditure-side models of GDP

4.5.1. Introduction

The expenditure-side econometric model of the determinants of GDP is based on the national income identity presented in Equation 3. GDP ($Y$) is a function of consumption expenditure ($C$) by firms and households, government spending ($G$), investment ($I$), plus exports ($X$) less imports ($M$). To isolate the impact of load shedding on GDP we add a variable to capture the frequency and magnitude of load shedding ($LS$) to the standard identity so that:

\[ Y_t = \beta_0 + \beta_1 C_t + \beta_2 G_t + \beta_3 I_t + (\beta_4 X_t - \beta_5 M) + \beta_6 LS_t \]

where $t$ represents time, $\beta_0$ to $\beta_6$ are the estimated parameters, and $\beta_6$ specifically captures the impact of load shedding on GDP.

This is the theoretical basis of the econometric models used to produce our first two estimates of the CoLS.

4.5.2. Overview of data and data sources

**National GDP aggregates**

The expenditure-side econometric models of the determinants of GDP are both based on a quarterly series of the expenditure on gross domestic product and its sub-components, sourced from the South Africa Reserve Bank (Table 5). These are expressed in constant 2010 rand and are seasonally adjusted and annualised values.

**Industry-level series on gross-fixed capital formation**

To determine the cost of load shedding on GDP at a sector level, we replaced aggregate gross fixed capital formation (GFCF) with an industry-specific measure of GFCF, but only where it improved the model fit. Until 2016 the SARB published a quarterly series of GFCF for six sectors including mining and manufacturing (Table 5). We sourced the discontinued series from the SARB and interpolated annual series on GFCF (which is still published) to generate quarterly data for the remainder of the period (2016 to 2019).

**Load shedding variable**

We based our analysis on the top-down estimate of the magnitude of load shedding derived by Eskom’s system operator. For the regression analysis, we tested the explanatory power of the load shedding variable in various forms. The load shedding variable had the most explanatory power when expressed as a percentage of total quarterly electricity sales. This format shows how significant the amount of load shedding was in each quarter relative to overall electricity demand – which is an input to production. Monthly data on total domestic electricity sales was also supplied by Eskom and aggregated into quarters.
Table 5 Data and variables used for the expenditure-side model of GDP

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source and data code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Expenditure side GDP aggregates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP (Y)</td>
<td>SARB (KB06006D)</td>
<td>Expenditure on domestic product (including residual), seasonally adjusted and annualised, Rm, market prices, constant 2010 values. Quarterly data</td>
</tr>
<tr>
<td>Consumption (C)</td>
<td>SARB (KB06007D)</td>
<td>Final consumption expenditure by households</td>
</tr>
<tr>
<td>General Government (G)</td>
<td>SARB (KB06008D)</td>
<td>Final consumption expenditure by general government</td>
</tr>
<tr>
<td>Gross Fixed Capital Formation (I)</td>
<td>SARB (KB06009D)</td>
<td>Gross fixed capital formation</td>
</tr>
<tr>
<td>Imports (M)</td>
<td>SARB (KB06014D)</td>
<td>Imports of goods and services,</td>
</tr>
<tr>
<td>Exports (X)</td>
<td>SARB (KB06013D)</td>
<td>Exports of goods and services,</td>
</tr>
<tr>
<td>Inventories (S)</td>
<td>SARB (KB06010D)</td>
<td>Change in inventories</td>
</tr>
<tr>
<td>Gross fixed capital formation for selected industries (I)</td>
<td>SARB GFCF manufacturing (NRI6082D), GFCF Electricity and water (NRI6085D). Annual series (6082Y) and (6085Y)</td>
<td>Quarterly data on GFCF by type of economic activity seasonally adjusted and annualised rates, Rm, market prices, constant 2010 values. Values between 2016 and 2020 were interpolated from annual series.</td>
</tr>
<tr>
<td><strong>Load shedding data</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Load shedding as a % of total sales (LS)</td>
<td>Derived from Eskom data (see below)</td>
<td>Monthly data aggregated into quarters</td>
</tr>
<tr>
<td>Load shedding</td>
<td>Top-down, Eskom system operator</td>
<td>Monthly data on the national estimate of the magnitude of load shedding in GWh aggregated into quarters.</td>
</tr>
<tr>
<td>Total electricity sales</td>
<td>Eskom: SAP Total Consumption (kWh)</td>
<td>Monthly national sales data in kWh (excl. international sales) aggregated into quarters from 2006 until 2019.</td>
</tr>
<tr>
<td>Dummy variables (D)</td>
<td>2008/9 financial crisis, drought, rains, credit boom and oil-price shock</td>
<td>Dummy variables were included for drought in 2Q06, 3Q06, 1Q18, 2Q18, rainy season 2017, global financial crisis 2008/9 and oil-price shock 2007.</td>
</tr>
</tbody>
</table>

4.5.3. Approach to estimating the CoLS based on a classic linear regression model (CLRM)

Our initial hypothesis was that load shedding was likely to have had a noticeable negative impact on GDP growth in the 16 quarters when it historically occurred. Since the impact of load shedding is likely to be fairly immediate, we felt it would probably be more evident in the quarter-on-quarter growth in GDP (as opposed to in level or year-on-year change).

To test this hypothesis, we began with a simple visual inspection of the relationship between historical load shedding episodes and quarter-on-quarter GDP growth (Figure 11). We note while the latter two periods of load shedding were associated with negative GDP growth, quarter-on-quarter growth remained positive in the first period (2007/8). Viewed against the linear trend in quarter-on-quarter GDP growth, growth was consistently below trend when load shedding...
occurred. It also appears that more severe episodes of load shedding were associated with a bigger
decline in growth and that the impact occurs within the same quarter – it is most evident in the
quarters when load shedding occurred. In other words, the impact is not significantly delayed.

Figure 11 Change in GDP against load shedding as a percentage of total electricity sales

This suggested that we should find a negative correlation between historical load shedding
episodes and GDP growth if we estimated the relationship econometrically. It also appears, based
on visual inspection that load shedding had a noticeable impact on GDP growth in the 16 quarters
when it occurred.

Transformation of variables for the classic linear regression model (CLRM)

To adhere to the assumptions of the classic linear regression model, the GDP aggregates which all
trend with time need to be transformed into a stationary series that are mean reverting. As such,
we express all the GDP aggregates in quarter-on-quarter changes, which as explained above is
likely to produce a better result than year-on-year changes which are influence by base effects. The
load shedding variable was expressed as a percentage of total electricity sales.

We estimated 11 separate single equation regression, one for total GDP and then a regression for
each of the ten individual sectors of the economy, as reported in the system of national accounts.
For each regression, we only include the subcomponents of GDP that were statistically significant
and improved the overall model fit.
The reserve bank does not publish the sub-components of expenditure on GDP at an industry level, except for GFCF, so most industry-level equations include national consumption aggregates. The specification of each equation is summarised in Appendix D, App Table 6. The final regression equation to estimate the impact of load shedding on total GDP growth was specified as follows:

**Equation 4**

\[
Y_t = \beta_0 + \beta_1 C_t + \beta_2 G_t + \beta_3 I_t + \beta_4 LS_t + \beta_5 D_{0t} + \epsilon_t
\]

where:

- \(Y_t\) = Quarter-on-quarter % change in GDP
- \(\beta_t\) = Constant
- \(C_t\) = Quarter-on-quarter % change in final consumption expenditure
- \(I\) = Quarter-on-quarter % change in gross fixed capital formation
- \(LS\) = Load shedding in GWh as a percentage of total electricity sales
- \(D_{0t}\) = Dummy variable for the 2008/09 financial crisis dummy
- \(\epsilon_t\) = Error term (residual)

4.5.4. **Approach to estimating the CoLS based on an auto-regressive distributed lag model**

Where the explanatory variables in a regression model are non-stationary (i.e. trending over time), and the interest is in understanding the long-run relationship between them, it more appropriate to use specialist time series techniques, such as the ARDL to estimate the coefficients than a classic linear regression. The reason for this is that in order to be able to estimate them with a CLRM, one has to difference the series to remove the trend (to avoid the problem of spurious regression between trending series) but in doing so one loses information about the long-term relationship between the trending series.

**Figure 12 Trend in real GDP and load shedding in GWh, 2007 to 2019**

![Figure 12 Trend in real GDP and load shedding in GWh, 2007 to 2019](image)

Source: Nova Economics analysis based on data from SA Reserve Bank and Eskom
Since we are more interested in the immediate short-term relationship between GDP growth and load shedding and are less concerned about accurately estimating the long-run relationship between GDP and its subcomponents, we felt the classic linear regression model (CLRM) would give us the best results but we have presented the results of the ARDL estimation as an alternative. Based on simple visual inspection of the relationship between historical load shedding episodes and the trend in real GDP, it is clear that as one would expect, load shedding incidents had little direct influence on the overall trend in GDP but would rather have had some influence in the variation in GDP around its long-term trend (Figure 12).

**Transformation of variables for the autoregressive distributed lags (ARDL) approach**

For the ARDL model, we include GDP and its sub-aggregates which all trend with time and need to be transformed into stationary series that are mean reverting. As such, we express all the GDP aggregates in quarter-on-quarter changes, which as explained above is likely to produce a better result than year-on-year changes which are influence by base effects. For the ARDL model, we distinguish between dynamic regressors (those that trend with time) and fixed regression including the dummy variables and load shedding series. We expressed all the dynamic regressors in a logarithmic form (by taking the natural logarithms of the underlying series) to make the estimated coefficients easier to interpret.

We expressed load shedding variable as a percentage of total electricity sales and estimated 11 single equation regression - one for each of the ten individual sectors of the economy and another for total GDP as reported in the system of national accounts. For each regression, we only include the subcomponents of GDP that were statistically significant and improved the overall model fit. The reserve bank does not publish the sub-components of expenditure on GDP at an industry level, except for GFCF, so most industry-level equations include national consumption aggregates. The specification of each equation is summarised in Appendix D. The final regression equation for total GDP was estimated using an ARDL model as follows:

**Equation 5**

\[
\ln (Y_t) = \ln (\beta_0) + \beta_1 \ln (C_t) + \beta_2 \ln (G_t) + \beta_3 \ln (I_t) + \beta_4 \ln (LS_t) + \beta_5 \ln (D_{0t}) + \epsilon_t
\]

where:
- \(Y_t\) = Real GDP, Rm, seasonally adjusted and annualised
- \(\beta_t\) = Constant
- \(C_t\) = Final consumption expenditure by households
- \(G_t\) = Final consumption expenditure by government
- \(I\) = Gross fixed capital formation
- \(LS\) = Load shedding in GWh as a percentage of total electricity sales
- \(D_{0t}\) = Dummy variable for the 2008/09 financial crisis dummy
- \(\epsilon_t\) = Error term (residual)
4.6. Estimation of the CoLS based on an energy-augmented Cobb-Douglas production function

4.6.1. Introduction

Our third estimate of the CoLS was estimated using a panel data regression model based on the Cobb-Douglas production function (Equation 6). In terms of this standard theory of economic production, industries combine inputs including capital (K), labour (L), and Hicks-neutral technology (A) to produce output (Y) or gross domestic product (GDP) (Equation 6). This standard production function can be augmented to include total national electricity sales (E) since power is also an input to production.

**Equation 6**

\[ Y_{it} = A_{it}K_{it}^{\alpha}L_{it}^{\beta}E_{it}^{\theta} \]

where:

- \( Y_{it} \) = Real GDP, Rm, seasonally adjusted and annualised
- \( A_{it} \) = Hicks neutral technology
- \( K_{it} \) = Fixed capital stock
- \( L_{it} \) = Labour (formally employed)
- \( E_{it} \) = Total domestic electricity sales (in GWh)

and \( i \) represents the different sectors of the economy and \( t \) represents time and there are constant returns to scale so that \( \alpha = 1 - \delta \).

We took the natural logarithm of the variables in Equation 7 so that we could estimate the equation using a panel regression technique known as the Fixed Effect Least-Squares Dummy Variable (LSDV) Model:

**Equation 7**

\[ \ln(Y_{it}) = A_{it} + \alpha \ln(K_{it}) + \delta \ln(L_{it}) + \theta \ln(E_{it}) + \varepsilon_t \]

Following the approach used by Burger et al.,\(^48\) we estimate the Cobb-Douglas production function as a system and isolate the contribution of load shedding to the change in GDP, rather than individually estimating single-equations for GDP and each of the ten sectors of the economy. The systems approach has some advantages over the single equation approach as it allows the simultaneous identification of factor-augmenting technical change and the contribution of electricity consumption, capital, and labour to GDP growth across all sectors.

We initially tried to isolate the influence of load shedding on GDP by augmenting the Cobb-Douglas production function with a single series representing the incidence and magnitude of load at a national level. We experimented by including it in various forms (in levels, as a dummy variable and expressed as a percentage of sales), but it was not possible to isolate the immediate and short-term effect of load shedding on GDP. This is probably because all the other variables included in the panel were slow-moving aggregates that are expressed in levels and overall load shedding has

little bearing on the long-term trend in GDP when compared to the influence of growth in the capital stock and employment.

We then approached the estimation of load shedding using the panel approach from a different perspective - and augmented the production function with total electricity sales. Since total electricity consumption is an input to production and is a slow-moving aggregate, it is possible to isolate the contribution of electricity to GDP growth within the production function. We then use the long-term relationship between electricity consumption and GDP to estimate the proportion of output that is being lost when load shedding occurs.

We illustrate the relationship between the trend in the normalised capital stock, labour, electricity consumption and GDP series for the Manufacturing industry in Figure 13. If we had attempted to estimate a single-equation production for the Manufacturing industry based on these series, the estimated parameters would only be based on the time-series variation between these four series.

![Figure 13 Manufacturing industry production function variables, normalised (2003=100)](image)

Source: Nova Economics analysis

The trends in the series for this industry suggest that while all three of the explicit inputs to manufacturing sector GDP has been in trend decline over the past decade, manufacturing GDP remained relatively stable, suggesting that total factor productivity increased (for example through gains in energy efficiency and/or labour productivity). By pooling the data and estimating the coefficients on capital, labour, electricity and productivity across all ten industries, estimated parameters are based on the much richer variation between industries and across time and are therefore likely to be far more efficient and reliable.
### 4.6.2. Overview of data and data sources

A summary of the data sources and variables used to estimate the Cobb-Douglas production function is provided in Table 6.

**Table 6 Data sources and variables- Cobb-Douglas production function**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source and data code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP (Y)</td>
<td>South African Reserve Bank (SARB) KBP6006D</td>
<td>• Expenditure on domestic product (including residual), seasonally adjusted and annualised rates, (\text{Rm, market prices, constant 2010 values. Quarterly data.})</td>
</tr>
<tr>
<td>Capital (K): Fixed Capital Stock Gross Fixed Capital Formation Quarterly gross fixed capital formation (GFCF)</td>
<td>SARB: KBP6140Y-KBP6148Y SARB: KBP6080Y-KBP6088Y SARB: NRI6081/2/5/8D, NRI6091/4D</td>
<td>• Fixed capital stock: seasonally adjusted and annualized, (\text{Rm, market prices, constant 2010 values.}) • Quarterly data on GFCF by type of economic activity seasonally adjusted and annualised rates, (\text{Rm, market prices, constant 2010 values.})</td>
</tr>
<tr>
<td>Labour (L)</td>
<td>Post-Apartheid Labour Market Series (PALMS) StatsSA: QLFS and LFS</td>
<td>• Number of labourers formally employed in each industry.</td>
</tr>
<tr>
<td>Total electricity sales by industry</td>
<td>• Eskom distribution monthly sales and revenue data reported for each region at 5-digit SIC level or higher, 2006 to 2019 • Eskom distribution, historical monthly sales and revenue series, national, 2003 to 2008 • Aggregate monthly sales data reported by major Eskom customer category 2006 to 2019 • States of SA cities report 2006, 2011 and 2014/15, breakdown of municipal electricity sales by industry.</td>
<td>Derived from a combination of the following data sets: • Disaggregated electricity sales and revenue data (classified in most cases at the 5-digit SIC code) for each of Eskom’s regions and its top customers, extracted from Eskom’s billing system for the years 2006 to 2019. • Disaggregated national sales and revenue data (classified in most cases at the 5-digit SIC code) sourced from Eskom distribution for the years 2003 to 2008. • Total monthly national sales data by customer category, extracted from SAP system. Categories include IPPs, Agri, Distributors, Commercial, Industrial, Int. Sales, Mining, Prepayment, Public lights, Residential, Traction, external and internal sales. • Municipal sales by industry as reported in SA Cities report and by CoUE report for 13 large municipalities for 2006, 2011, 2014/15.</td>
</tr>
</tbody>
</table>
Gross domestic product

The output series used to estimate the production function is the SARB’s quarterly expenditure series on real gross domestic product (including residual) at seasonally adjusted and annualised values.

Capital stock

Following the method used by Burger et al., we derived a quarterly series of capital stock for the ten industries used in the national accounts based on data sourced from SARB. Further detail on the method used to derive the series can be found in Appendix C.1. This is included the annual real fixed capital stock by industry (seasonally adjusted and annualised) and the quarterly gross fixed capital formation series, by industry where available. The SARB used to publish a quarterly gross fixed capital formation series for six of the ten industries defined in the national accounts but this was discontinued in 2015. For the industries and the years where quarterly gross fixed capital formation (GFCF) was not available, quarterly figures for fixed capital stock were created by interpolating the values in the annual series using cubic spline and moving average techniques.

In Figure 14 we present the accumulation of capital by industry. As seen, most of the growth in capital stock over the past decade has been in the electricity, transport, personal and financial services industries. Capital stock in the mining industry, by contrast, has declined.

![Figure 14 Trend in quarterly fixed capital stock, by industry, 2000 to 2019](image)

Source: Nova Economics analysis based on data from SA Reserve Bank

49 Kreuser, Burger, and Rankin, “The elasticity of substitution and labour-displacing technical change in post-apartheid South Africa.”
Labour

The labour data used in the study is taken from the Post-Apartheid Labour Market Series (PALMS) 1994-2019Q2 compiled by DataFirst (UCT) from Statistics South Africa’s (StatsSA) Labour Force Survey (LFS) and Quarterly Labour Force Surveys (QLFS) till Q2 2019, whereafter the QLFS from StatsSA were used for Q3 and Q4 of 2019.

The LFS is a biannual series that ran from 2000 to 2007. We interpolated the biannual series to create a quarterly series. From 2008 StatsSA ran a quarterly labour force survey and we use the employment series from this publication until the end of 2019.

Many papers have investigated the problems in comparing the StatsSA household surveys and particularly the effect that modifications in questionnaire design and sampling methodology may have had on the comparability of the household surveys over time. The most serious comparability problems occur for the informal sector or self-employed workers so the effect of these inconsistencies can be limited by omitting these workers from the sample and restricting our dataset to formal sector employees only.\(^\text{50}\)

After omitting all the unemployed, economically inactive, and self-employed workers from the dataset, aggregate industry employment per period is calculated from the individual responses to the questions regarding the industry of employment and the survey weights. We look at this data at an industry level, using the SIC one-digit categories to group the data into ten industries, and many of the measurement issues are ameliorated by aggregation.

The ten industries are therefore used as the cross-sectional units of observation for our production function model. Many papers have reported issues in comparing labour force data over time due to changes in survey design and sampling methodology. The most serious compatibility issues are in the series on the informal sector and self-employed workers, so most studies recommend omitting these categories of workers from the sample so that employment trends reflect only formal sector employment.\(^\text{51}\) We, therefore, omit all the unemployed, economically inactive, and self-employed workers from the dataset.

We estimated total formal sector employment by industry by aggregating individual responses to the survey and by applying the relevant survey weights. Employment data was classified into industries using SIC codes at the 2-digit level, to be comparable to industries as defined in the South African system of national accounts.

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\(^{50}\) Kreuser, Burger, and Rankin, “The elasticity of substitution and labour-displacing technical change in post-apartheid South Africa.”

\(^{51}\) Kreuser, Burger, and Rankin, “The elasticity of substitution and labour-displacing technical change in post-apartheid South Africa.”
Electricity sales

To augment the production function with electricity sales, we had to derive electricity sales by industry (classified according to SIC code at the 2-digit level) so that we could regress this against GDP (also reported by industry at the 2-digit SIC code level). To derive an electricity sales series by industry, we made use of the following three sets of data provided by Eskom distribution, extracted from the Eskom billing system:

1. Highly disaggregated electricity sales and revenue data classified in most cases at the 5-digit SIC code for each of Eskom’s 6 regions and its top customers, extracted from the billing system at Eskom distribution for the years 2006 to 2019.
2. Highly disaggregated national sales and revenue data (classified in most cases at the 5-digit SIC code) sourced from Eskom distribution for the years 2003 to 2008.
3. Aggregated total monthly national sales data by major Eskom customer category, extracted from SAP system at Eskom distribution from 2006 to 2019.

A breakdown of 13 major municipal redistributors’ electricity sales, as reported in various editions of the SA State of Cities report, was also used to allocate the ~40% of Eskom’s direct sales that are sold to municipal distributors’ industries. An explanation of the step-by-step process we followed to derive electricity sales by industry is presented in Appendix D.

Figure 15 Electricity sales by industry, seasonally adjusted

Source: Nova Economics analysis based on data provided by Eskom

5. Results

5.1. Introduction

In this chapter, we report the results of the three approaches we have taken to estimating the cost of load shedding (CoLS). Our primary estimate of the CoLS was produced using a classic linear regression model (CLRM). In the CLRM specification, all trending variables were expressed in first differences and regressed against quarter-on-quarter change in GDP rather than in levels. As we found this specification worked best to isolate the short-to-medium term impact that load shedding had on GDP. We also, however, discuss the alternative estimates of the CoLS, which based on ARDL and panel regression methods.

5.2. National estimates of the cost of load shedding

5.2.1. The cost of load shedding in rand per kilowatt-hour

We estimated that the overall cost of load shedding is between R7.61/kWh and R9.53/kWh (in 2020 prices). Our estimates of the CoLS increased steadily over time – from R7.61/kWh during the first major episode of load shedding (2007-2008) to R9.53/kWh during the third period (2018 – 2019) (Table 7).

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost of load shedding (R/kWh)</td>
<td>7.61</td>
<td>8.80</td>
<td>9.53</td>
</tr>
<tr>
<td>Total load reduction (GWh)</td>
<td>872</td>
<td>1 724</td>
<td>1 307</td>
</tr>
<tr>
<td>Number of months in which load shedding occurred (frequency)</td>
<td>7</td>
<td>15</td>
<td>9</td>
</tr>
<tr>
<td>Number of months in which load shedding exceeded 300 GWh (severity)</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Source: Nova Economics analysis

This was contrary to our expectation that in the context of recurring electricity supply shortages the cost of load shedding (in kWh) would decrease, as electricity consumers have the opportunity and incentive to employ measures and tactics to reduce the cost of these disruptions. The increase in the CoLS over the three periods may be related to the increase in the frequency and/or severity of load shedding. Eskom estimates that it carried out a total of ~870 GWh of load shedding in the 2008-9 period as compared to ~1 700 GWh during 2013-15 and ~1 307 GWh in 2018-19. The month in which load shedding was most severe was March 2019.
5.2.2. The impact of load shedding on the South African economy

A detailed analysis of our primary estimates of the CoLS (based on the CLRM technique) show that load shedding subtracted up to 0.6 percentage points from quarter-on-quarter GDP growth in South Africa in the quarters when it occurred (Figure 16 and Figure 18). In the third quarter of 2015, the South African economy came close to entering a technical economic recession, when q/q GDP (at basic prices) did not expand, after contracting by 0.5% q/q in the second quarter. In the absence of load shedding, GDP growth would have remained positive on a q/q basis throughout 2015 (Figure 16).

We estimate that load shedding cost the South African economy a total of R34.5 billion (in 2020 values) between 2007 and the end of 2019 (Figure 17). In the second quarter of 2015, Eskom implemented an estimated 809 GWh of load shedding, making it the quarter with the most load shedding to date (Figure 18 and Figure 19). During the second quarter of 2015, 809 GWh of load shedding was imposed, which subtracted 0.6 percentage points from q/q GDP growth and cost the economy R7 billion in GDP.

Source: Nova Economics analysis

Figure 16 The impact of load shedding on quarterly GDP growth, 2007 to 2019

![Graph showing the impact of load shedding on quarterly GDP growth, 2007 to 2019.]

Source: Nova Economics analysis

Figure 17 Impact of load shedding on GDP (rand billion, constant 2020) by period

<table>
<thead>
<tr>
<th>Period</th>
<th>Impact on GDP (R bn, constant 2020 prices)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007-2008</td>
<td>-6.66</td>
</tr>
<tr>
<td>2013-2015</td>
<td>-15.25</td>
</tr>
<tr>
<td>2018-2019</td>
<td>-12.59</td>
</tr>
</tbody>
</table>

Source: Nova Economics analysis
Figure 18 Impact of load shedding on GDP growth q/q

Change in q/q GDP attributed to load shedding (percentage points)

<table>
<thead>
<tr>
<th>Period</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>-0.08</td>
<td>-0.27</td>
<td>-0.04</td>
<td>-0.01</td>
<td>0.00</td>
<td>-0.02</td>
<td>0.00</td>
<td>-0.16</td>
</tr>
<tr>
<td>2008</td>
<td>-0.32</td>
<td>-0.63</td>
<td>-0.18</td>
<td>-0.26</td>
<td>-0.20</td>
<td>-0.01</td>
<td>0.00</td>
<td>-0.49</td>
</tr>
<tr>
<td>2013</td>
<td>-0.27</td>
<td>-0.03</td>
<td>-0.01</td>
<td>0.00</td>
<td>-0.02</td>
<td>0.00</td>
<td>-0.16</td>
<td>-0.42</td>
</tr>
</tbody>
</table>

Source: Nova Economics analysis

Figure 19 Impact of load shedding on GDP (rand billion, constant 2020)

GDP (R bn, constant 2020 prices)

<table>
<thead>
<tr>
<th>Period</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>-0.78</td>
<td>-3.20</td>
<td>-2.68</td>
<td>-2.08</td>
<td>-2.92</td>
<td>-2.28</td>
<td>-7.16</td>
<td>-5.69</td>
</tr>
<tr>
<td>2008</td>
<td>-0.30</td>
<td>-0.06</td>
<td>-0.44</td>
<td>-2.92</td>
<td>-2.28</td>
<td>-7.16</td>
<td>-4.84</td>
<td>-5.69</td>
</tr>
<tr>
<td>2013</td>
<td>-0.06</td>
<td>-0.44</td>
<td>-2.92</td>
<td>-2.28</td>
<td>-7.16</td>
<td>-4.84</td>
<td>-5.69</td>
<td>-5.69</td>
</tr>
<tr>
<td>2014</td>
<td>-0.21</td>
<td>-0.30</td>
<td>-0.06</td>
<td>-0.44</td>
<td>-2.92</td>
<td>-2.28</td>
<td>-7.16</td>
<td>-4.84</td>
</tr>
<tr>
<td>2015</td>
<td>-0.03</td>
<td>-0.30</td>
<td>-0.06</td>
<td>-0.44</td>
<td>-2.92</td>
<td>-2.28</td>
<td>-7.16</td>
<td>-4.84</td>
</tr>
<tr>
<td>2018</td>
<td>-0.03</td>
<td>-0.30</td>
<td>-0.06</td>
<td>-0.44</td>
<td>-2.92</td>
<td>-2.28</td>
<td>-7.16</td>
<td>-4.84</td>
</tr>
<tr>
<td>2019</td>
<td>-0.03</td>
<td>-0.30</td>
<td>-0.06</td>
<td>-0.44</td>
<td>-2.92</td>
<td>-2.28</td>
<td>-7.16</td>
<td>-4.84</td>
</tr>
</tbody>
</table>

Source: Nova Economics analysis
5.2.3. Alternative estimates of the CoLS

As mentioned, our primary estimates of the CoLS were calculated using a classic linear regression model (CLRM). We expressed all model variables (except for load shedding and dummy variables) in first differences (i.e., in quarter-on-quarter percentage change).

We also produced alternative estimates of the CoLS using two different econometric techniques - an ARDL model of the expenditure-side GDP model and a panel regression where we estimate the relationship between electricity consumption and GDP across 10 different industries using the fixed effects, least-square dummy variable (LSDV) technique.

If the underlying variables in a regression model are non-stationary (i.e., trend over time) the goal is usually to understand whether there is a long-run relationship between these variables. In such cases, it is more appropriate to use specialist time series techniques, such as the ARDL to estimate the coefficients, as opposed to a classic linear regression model (CLRM). Since we were interested in isolating the impact of load shedding (a stationary variable) on GDP growth in the short-term, we favour the CLRM results.

The estimated CoLS, based on our ARDL results, varied between R5.26/kWh and R6.59/kWh (Table 8). Our specification of the ARDL was based on the same theoretical model as the CLRM. The resulting estimate of CoLS, however, was ~30% lower than our primary estimates (based on the CLRM). We believe the ARDL technique underestimates the impact of load shedding on GDP, perhaps because it is better suited to estimating the long-run relationship between slow-moving non-stationary time series variables. We have provided a detailed description of the ARDL regressions in Appendix D.

<table>
<thead>
<tr>
<th>Period</th>
<th>Primary estimate</th>
<th>Alternative estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CLRM</td>
<td>ARDL</td>
</tr>
<tr>
<td>2007-08</td>
<td>7.61</td>
<td>5.26</td>
</tr>
<tr>
<td>2013-15</td>
<td>8.80</td>
<td>6.09</td>
</tr>
<tr>
<td>2018-19</td>
<td>9.53</td>
<td>6.59</td>
</tr>
</tbody>
</table>

We also estimated the CoLS based on the Cobb-Douglas production function, following the approach used by Burger et al.,\textsuperscript{53} using a panel regression. This approach is more suited to determining the long-term relationship between electricity consumption and GDP growth across all ten industries. We used the estimated long-term relationship between electricity consumption and GDP to infer what proportion of GDP would have been lost due to load shedding.

\textsuperscript{53}Kreuser, Burger, and Rankin
This systems approach has some advantages over the other single equation methods (i.e. CLRM and ARDL) as it uses both the time-series variation within industries and the variation across industries to simultaneously identify factor-augmenting technical changes and the contribution of electricity consumption, capital, and labour to GDP growth across all sectors.

The estimates of the total national CoLS based on the panel regression were lower than our primary estimates ranging between R2.86/kWh and R3.58/kWh (Table 8). As was the case with the estimates based on the ARDL technique, we believe our estimates of the CoLS inferred from the panel regression are underestimates. This is likely because the influence of load shedding on GDP had to be inferred systems, as it could not be estimated directly using the systems approach. We believe our estimates of the relationship between electricity, labour, capital and GDP growth are robust. We are, however, less confident in the inferred amount of output that would be lost during load shedding (based on the long-term direct relationship between electricity consumption and economic activity). We have provided a detailed description of the panel technique in Appendix C.

Comparing the three estimates of CoLS (Figure 20), we find that the CLRM estimate is consistently the largest, which suggests that the ARDL and panel techniques may understate the impact of load shedding. All three estimates of the CoLS increased over time.

**Figure 20 Cost of load shedding by periods and estimation method (R/kWh, 2020 constant prices)**

Source: Nova Economics analysis
5.2.4. Comparison with previous load shedding estimates

We also compare our primary estimate of the CoLS to the estimate produced by Deloitte in 2009 (Table 9). Our primary estimate of the CoLS in 2007 - 2008 at R7.61/kWh is similar to the forward-looking estimate produced by Deloitte in their ‘realistic load shedding scenario’ which was R8.95/kWh (inflated to 2020 values).\(^{54}\) We compare the values for the 2007-08 period since the Deloitte study was conducted in 2009.

Table 9 Comparison of our primary estimate of the CoLS with Deloitte 2009

<table>
<thead>
<tr>
<th>(\text{Deloitte estimates (R/kWh)})</th>
<th>(\text{Our estimates (R/kWh)})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\text{Estimate})</td>
<td>(\text{2008 values})</td>
</tr>
<tr>
<td>Realistic scenario</td>
<td>4.92</td>
</tr>
</tbody>
</table>

5.3. The impact of load shedding by industry

5.3.1. Cost of load shedding by industry (in R/kWh)

The impact of load shedding is not uniformly distributed across the ten sectors of the economy that are defined in the national accounts. In Figure 21 we have illustrated the proportion of the total national cost of load shedding (in R/kWh) attributed to each of the sectors of the economy. We were able to estimate the cost of load shedding for every sector except for the mining industry.\(^{55}\) The results of the single-equation regression estimates of the CoLS for each industry are summarised in Appendix D.

Our results show that four of the nine sectors, namely manufacturing, transport and communication, retail trade and agriculture bore just over 80% of the total national cost of load shedding (expressed in rand of GDP lost for every kilowatt-hour of load shedding, i.e. R/kWh). The manufacturing sector alone bore nearly 40% of the total cost of load shedding.

The extent to which an individual industry bears the cost is a function of its size, the electricity intensity of the sector and the ability of firms in the sector to adapt to or mitigate against electricity supply interruptions. For example, during the most recent period of load shedding, the manufacturing sector lost R3.85 worth of output for every kWh of nationwide rotational load shedding that occurred (~40% of the overall CoLS). By contrast, the financial and business services

\(^{54}\) Deloitte, “Modelling the impacts of electricity disruptions, Chapter 3, Report on Eskom and the Electricity Sector.”

\(^{55}\) A reliable estimate of the impact of load shedding on mining GDP could not be obtained as it was not possible to control for more than 10% of the variation in the highly volatile quarter-on-quarter growth in Mining GDP.
sector lost only R0.07/kWh (~1% of the overall CoLS) while community and personal services sector did not suffer any loss.  

**Figure 21 Contribution of each sector to the total cost of load shedding (R/kWh)**

Weighting the contribution of each sector to the total CoLS by its share in GDP (normalised CoLS) shows that the agriculture industry, which is a relatively small contributor to total GDP (3.6%), was the sector most adversely affected by load shedding. The normalised CoLS for the agriculture industry was 4.2 times that of the average (R1/kWh). Manufacturing and utilities lost three times more output than the average industry while output in the financial and business and community, social and personal services industries emerged largely unscathed. This suggests that it was the more energy-intensive primary and secondary industries that were the most adversely affected by load shedding.

5.3.2. Normalised costs of load shedding

We provided a summary of the cost of load shedding by industry, normalised by each industry’s respective contribution to total GDP (Figure 22 and Figure 23).

Weighting the contribution of each sector to the total CoLS by its share in GDP (normalised CoLS) shows that the agriculture industry, which is a relatively small contributor to total GDP (3.6%), was the sector most adversely affected by load shedding. The normalised CoLS for the agriculture industry was 4.2 times that of the average (R1/kWh). Manufacturing and utilities lost three times more output than the average industry while output in the financial and business and community, social and personal services industries emerged largely unscathed. This suggests that it was the more energy-intensive primary and secondary industries that were the most adversely affected by load shedding.

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56 Our primary regression analysis indicated that the relationship between load shedding and GDP growth was not statistically significant from zero.
5.3.3. Impact of load shedding on GDP growth by industry

In Figure 24 we have illustrated the impact of load shedding GDP growth by industry. Our estimates suggest that the Agricultural sector, which was the worst affected, lost over 5% of its output because of load shedding between 2013 and 2015. Load shedding was not the only factor responsible for the contraction in agricultural output over that period but it was a significant contributor (Appendix E: App Figure 8).
The other sectors that experienced a significant contraction in output due to load shedding (more than 2% over the 2013 to 2015 period) are Manufacturing, Electricity & Water and Transport and Communications. Further figures illustrating the impact of load shedding on the trend in quarterly GDP growth for these and other sectors can be found in Appendix E.

### 5.3.4. Impact of load shedding on GDP, by industry in billions of rand

While agriculture suffered the biggest losses due to load shedding relative to its contribution to GDP, the manufacturing industry lost the largest amount in absolute terms – a total of R11 billion in GDP between 2007 and 2019.
The cost of unserved energy (CoUE) is widely used internationally as a proxy for the cost of infrequent unplanned outages. The CoUE is, in essence, a measure of each sector’s electricity intensity— the rand of output the sector produces for every kWh of electricity consumed. The estimates of the CoUE however, are not directly comparable with the cost of regular planned outages (e.g. cost of load shedding) because they don’t account for differences in an industry or firms inherent resilience planned outages or their ability to adapt to and mitigate against the damages.

The CoUE suggests that it is the least electricity-intensive industries that would lose the most output per kWh of electricity lost during a power outage. Our estimates of the CoLS suggest that the opposite is true (Figure 26 and Figure 27). Energy-intensive sectors like mining, manufacturing and agriculture are highly dependent on electricity for production, have fewer alternatives and are likely to suffer much greater losses than more services-oriented industries like finance and business services.
Note: A reliable estimate of the impact of load shedding on mining GDP could not be estimated as it was not possible to control for more than 10% of the variation in the highly volatile q/q growth in Mining GDP.

Source: Nova Economics analysis

The difference between the two estimates is the most evident at the extreme: the least energy-intensive industry, finance and business services, and most electricity-intensive industries such as manufacturing. The CoUE for finance and business services is R390/kWh, this means that for every unit of electricity the sector consumes it generates R390 worth of output. The assumption is that if an unplanned outage were to occur it would lose R390 for every kWh of electricity that was not provided. By contrast, the CoUE suggests that manufacturing would lose roughly a sixth of the output of the finance sector for every kWh of load shedding occurred (R67/kWh).
This is not likely to be the case as the nature of the finance industry is that it is inherently quite resilient to power outages. For example, many finance and business professionals would be able to continue working on their battery-powered laptops, key IT systems would have back-up power generation installed and some office buildings have back-up generation. Alternatively, people will simply shift their workload to a later time.

Our estimate of the CoLS for the finance and business services sector (normalised), which is based on the historical variance in sectoral GDP and therefore include differences in the inherent ability of industries to adapt and mitigate costs, suggests that the normalised CoLS for the manufacturing sector is R2.85/kWh and is 95 times higher than the normalised CoLS for the finance industry which is just 3 cents per kWh (R0.03/kWh).

5.3.6. Putting the economic cost of load shedding in perspective

Load shedding cost the South African economy nearly R35 billion in the 12 years between 2007 and 2019. Had all the load shedding experienced over the period taken place in a single quarter in 2019, it would have resulted in a 5% contraction real GDP growth (q/q%). To put this figure into perspective the total cost of load shedding at R35 billion is roughly equivalent to the impact the 2008/9 financial crisis had on GDP growth (it also subtracted a cumulative five percentage points from quarter-on-quarter GDP growth but over a much shorter period (Figure 28)).

Figure 28 Impact of load shedding on GDP growth, compared to Covid-19 and the financial crisis

Source: Nova Economics analysis based on seasonally adjusted and annualised time series GDP data from StatsSA.

The Covid-19 pandemic, however, resulted in a larger contraction in GDP in just one quarter - the second quarter of 2020, when GDP fell by over 15% q/q than the combined impact of load shedding on GDP over the past 12 years – which is equivalent to roughly a 6% q/q drop in GDP if it occurred in a single quarter. The contraction in South African GDP in the second quarter of 2020 which was precipitated by the Covid-19 pandemic was, however, the most severe contraction the SA economy has experienced since the Second World War.
5.4. Caveats to the results

5.4.1. Our estimates of the CoLS are conservative because they exclude longer-term impacts of load shedding on potential GDP growth

Our estimates of the CoLS capture the impact of load shedding as reflected in the variation in GDP growth around its long-term trend. This includes the direct and indirect damages (e.g. loss of output) and the costs of adaptation and mitigation (e.g. higher input costs such as investment in back-up generation). However, they can still be considered conservative estimates because they exclude the longer-term impact of recurring outages on business and investor confidence.

In an announcement on the 20th of March 2020, credit rating agency Moody’s noted that “Unreliable electricity supply ... continue[s] to constrain South Africa’s economic growth” \(^{57}\). Similarly, in April 2020, Standard and Poor’s noted “In the second half of 2019, the economy shrank, due partly to a set of severe rolling power blackouts,” and this was a factor in their confirmation of South Africa’s sub-investment grade sovereign credit rating. \(^{58}\)

As this would be reflected in lower longer-term GDP growth, not in the variation around the trend, it is not possible to identify this potential loss of output econometrically. While many factors have contributed to the gradual decline in GDP growth in South Africa over the past decade, there is little doubt that load shedding and persistent electricity supply constraints are among them.

5.4.2. We were only able to estimate the costs of load shedding at a macroeconomic level

While we were able to produce reliable estimates of the historical CoLS for nine of the ten sectors reported in South Africa’s national accounts, we cannot comment on the differences within these sectors – for example, the impact on transport vs. communication or the impact on tourism-related activities which are distributed across different sectors. Our estimates are based on the variation in macroeconomic aggregates and the data is not sufficiently disaggregated to comment on impact at a sub-industry or firm level.

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\(^{57}\) Moody’s, Moody’s downgrades South Africa’s ratings to Ba1, maintains negative outlook (2020). www.moodys.com/research/Moodys-downgrades-South-Africas-ratings-to-Ba1-maintains-negative-outlook--PR_420630.

6. Key insights and recommendations

6.1. The cost of load shedding – key insights

The purpose of this study was to provide Eskom with reliable and accurate estimates of the economic cost of load shedding. There were three distinct periods of load shedding: 1) October 2007 to April 2008, 2) November 2013 to October 2015, and 3) June 2018 to September 2020.

Our estimates suggest the CoLS increased steadily over time – from R7.61/kWh during the first major episode of load shedding (2007-2008) to R9.53/kWh during the third period (2018 – 2019). This was contrary to our expectation that in the context of recurring electricity supply shortages the cost of load shedding (in kWh) would decrease, as electricity consumers adapted and invested in back-up generation. The increase in the CoLS over the three periods may be related to the increase in the frequency and/or severity of load shedding. Eskom estimates that it undertook a total of ~870 GWh of load shedding in the 2008-9 period as compared to ~1 700 GWh during 2013-15 and ~1 307 GWh in 2018-19. The month in which load shedding was most severe was March 2019. Our estimates are similar to Eskom’s previous estimate of R8.95/kWh produced by Deloitte in 2009.

We estimate that load shedding cost the South African economy a total of R34.5 billion since 2007. Had all the load shedding experienced over these 12 years taken place in a single quarter in 2019, it would have resulted in a 5% contraction real q/q GDP growth. The put this into perspective, the impact of load shedding is more or less equivalent to the total impact of the 2008/9 financial crisis on the economy (which subtracted roughly 5 percentage points from trend q/q GDP growth over five quarters).

We also set out to assess how the cost of load shedding is distributed across different sectors of the economy. We produced estimates of the cost of load shedding for all sectors of the economy, except for the mining industry. As anticipated, we found that the cost of load shedding is unevenly distributed. During the third period of load shedding, four of the nine industries, worst affected by load shedding bore 80% of the total cost (measured in R/kWh) – namely manufacturing (SIC 3), transport and communication (SIC 6), wholesale and retail trade (SIC 5) and agriculture, hunting, forestry and fishing (SIC 1). The manufacturing sector alone shouldered nearly 40% of the total cost of load shedding.

The extent to which an individual industry bears the cost is a function of its size (i.e. contribution to total GDP), the electricity intensity of the sector, and the ability of firms in the sector to adapt to or

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59 Expressed in 2020 prices.
60 Expressed in 2020 prices.
61 Deloitte, “Modelling the impacts of electricity disruptions, Chapter 3, Report on Eskom and the Electricity Sector.”
62 Expressed in 2020 prices and for the period from 2007 until 2019.
63 A reliable estimate of the impact of load shedding on mining GDP could not be obtained as it was not possible to control for more than 10% of the variation in the highly volatile quarter-on-quarter growth in Mining GDP.
mitigate against unplanned electricity supply interruptions. We found that the less electricity-intensive and more service-oriented industries emerged relatively unscathed. For example, the financial and business services sector, which is the largest contributor to GDP but is not very electricity-intensive, lost just R0.07 per kWh of national load shedding during the most recent period (2018-19). This was less than 1% of the total cost of load shedding over the period. The community and personal services sector did not suffer any loss of GDP due to load shedding (the estimated CoLS was not statistically significant from zero).

There are several reasons why service-oriented and less electricity-intensive industries are inherently more resilient and better able to adapt to power outages. For example, professionals in the finance and business services industry can continue to work during power outages – the electronic equipment they rely on such as laptops central IT systems are fitted with back-up power generation sources. Working hours in this industry also tend to be more flexible so that people can shift their working hours to better accommodate load shedding.

We also normalised the cost of load shedding by each industry’s respective contribution to total GDP. The normalised estimates reveal which sectors were the most adversely affected by load shedding relative to their size. From this perspective, the agricultural sector was the most adversely affected by load shedding. While the agricultural industry is a relatively small contributor to national GDP (it accounts for 3.6% of total output) the normalised estimates of the CoLS show that it lost 4.2 times more output per kWh of load shedding than other industries, on average. Manufacturing (SIC 3) and utilities (SIC 4) lost three times more output than the average, while output in the financial and business (SIC 7) and community, social and personal services industries (SIC 8) were largely unaffected.

6.2. The potential uses of the CoLS estimates

It was envisaged that the updated estimates of the CoLS may provide insights about the distribution and magnitude of the cost of outages that could inform energy sector policy. Measures of the cost of outages are useful in assessing the relative costs of interventions to mitigate against the risk of load shedding, and so can be used to make socially optimal investment decisions.

Eskom and its shareholder face several choices when assessing how to mitigate against the risk of further load shedding (examples are provided in Table 10). There are several potential options to consider on both the demand and supply-side, but all of these interventions are associated with financial and/or broader economic costs.

On the supply-side, the immediate options are limited but would include running emergency generation or peaking plant (e.g. diesel-fired open cycle gas turbines) at higher load factors. On the demand-side immediate options may include power buybacks from customers under contract, voluntary curtailment by top customers or as a last resort emergency load shedding.

Over the short-to-medium term, several interventions can be considered. These may include decisions to return moth-balled plants to service, building or procuring modular utility-scale renewable capacity, investing in large-scale energy-efficiency and demand-side management
programmes or entering into new interruptible supply agreements. Other options that have been mooted in the past include procuring power from mobile power generating ships and entering co-generation agreements with domestic industry.

Table 10 Types of supply-side and demand-side interventions given persistent outages

<table>
<thead>
<tr>
<th>Category</th>
<th>Immediate</th>
<th>12-36 months</th>
<th>&gt;36 months</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply-side interventions</td>
<td>• Running OCGTs at high load factors.</td>
<td>• Return-to-service of a mothballed plant</td>
<td>• Grid extension by way of additional generation plants.</td>
</tr>
<tr>
<td></td>
<td>• Building modular utility-scale renewables capacity</td>
<td>• Power ships</td>
<td>• Building modular utility-scale renewables capacity.</td>
</tr>
<tr>
<td></td>
<td>• Co-generation agreements</td>
<td>• Postponing scheduled maintenance of plants.</td>
<td></td>
</tr>
<tr>
<td>Demand-side interventions</td>
<td>• Power buybacks</td>
<td>• Energy-efficiency demand-side management</td>
<td>• Energy-efficiency demand-side management</td>
</tr>
<tr>
<td></td>
<td>• Reducing demand from top customers under interruptible and curtailable load supply agreements</td>
<td>• Entering into interruptible load supply agreements</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Emergency load shedding</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Adapted from Deloitte, 2009

It is also important to consider who bears the costs. For example, if the system operator decides to run Eskom’s peaking plant (OCGTs) at higher load factors in a bid to avoid load shedding, Eskom bears the cost and must motivate to recover the costs from the consumer via a higher tariff.

While the cost of load shedding at R9.53/kWh is higher than the cost of running OCGTs estimated by EPRI\(^64\) at R1.99/kWh (2015 prices), it is borne mainly by the most energy-intensive sectors of the economy (e.g. manufacturing, mining, and transport, while Eskom itself only bears a small proportion of the cost (i.e. lost electricity sales).

De Nooij et al\(^65\) note that measures of the cost of outages are sometimes used to minimise the economic costs of outages by informing which customers should be disconnected from the grid. According to the representatives of Eskom, this is not practical in South Africa. Load shedding is implemented at a substation level, making it difficult to isolate specific sectors. Although top customers often have dedicated substations, most substations supply a large number of customers spanning a broad range of sectors.


\(^{65}\) de Nooij, Koopmans, and Bijvoet, “The value of supply security - the costs of power interruptionsL Economic input for damage reduction and investment in networks.”
References


Appendix A. Estimating the magnitude of load shedding.

A.1. Detailed approach to producing the top-down estimate

The top-down estimate of the magnitude of load shedding, supplied by Eskom’s system operator, is based on the difference between day-ahead forecasts of the national load profile and the actual demand profile over the days when load shedding took place (App Figure 1).

Eskom’s system operator produces forecasts of the residual electricity demand profile over the next 24-hour period, daily Actual observed demand is likely to be slightly lower or higher than the forecast- the difference between forecasted demand and actual demand on a given day is referred to as the forecast error. The difference between forecast and actual demand is depicted for an example day, 13 February 2019, with no load shedding (App Figure 2).
Since it is not possible to directly observe load shedding, the Eskom system operator accepts that it must be estimated. When load shedding takes place, the amount of "load shed" in GWh is estimated by calculating the difference between forecast demand and actual demand during load shedding. However, the system operator also adjusts this estimate for the forecast error before and after load shedding took place.

The estimation of the forecast error is represented in App Figure 3, where it is assumed that load shedding took place between 9 am and 11 pm, for example. The actual forecast error was observed as 161 MWh at 8 am, and 543 MWh at midnight, based as the difference between forecast demand and actual consumption at 8 am, and midnight for this example day. The system operator derives a linear trend line between these two data points and estimates the forecast error for the hours where load shedding is experienced, represented in teal.
The system operator estimates load shedding by taking the difference between the actual demand and forecast demand during a load shedding event and accounting for the forecast error (App Figure 4).

Based on discussions with the team responsible for producing the forecasts at the system operator, we understand that day ahead forecast of residual demand is produced based on a statistical analysis of historic average trends in sales and variables that influence demand as well short-term actual consumption data from the recent past (last week/month/quarter). This means that the recent trends in sales including a decline in demand due to load shedding would be factored into the system operator estimate of future demand forecasts.

As a result, the magnitude of load shedding might be underestimated by the system operator. To validate the system operator’s estimate of the magnitude of load shedding, we calculated a second measure of the magnitude of load shedding, based on substation level data on the incidence of load shedding.
We calculated the bottom-up estimate of load shedding to independently estimate the magnitude of load shed in GWh and validate the system operator’s estimates. Our bottom-up estimate is calculated using historic electricity sales at a granular level and considers consumption patterns of various types of customers.

Eskom’s top customer segment consists of energy-intensive firms, mainly mining and industrial operations, which consume more than 100 GWh per annum. Stable and consistently reliable electricity supply is critical for Eskom’s top customers, given the energy-intensive nature of these customers operations. Top customers, therefore, enter into agreements with Eskom which regulates the quantity and stability of their electricity supply. These agreements often contain provisions that top customers will not be subject to load shedding, but rather agree to load curtailments and power buybacks in the event the national grid is under pressure. Our bottom-up approach separately estimates load curtailment and power buybacks from top customers, and the magnitude of scheduled rotational load shedding to all other customers.
Estimate of the magnitude of load shedding for customers without load curtailment agreements

We obtained substation level monthly sales data from 2007 to 2019 (in GWh) from the distribution performance division. This data excluded sales to the top customer segment. A robust estimate of the magnitude of load shedding should look at what consumers would demand in the absence of load shedding. Demand modifications by customers solely as a result of load shedding being implemented should not factor into the estimate of the magnitude of load shedding. To account for potential demand modifications by consumers in periods with high incidences of load shedding, we attempted to estimate average consumption per month per substation based on two reference years without load shedding, (2016 and 2017). This gave us a baseline indication of what electricity consumption could be at a substation level in the absence of load shedding.

We then obtained a second dataset detailing all the incidences of load shedding per substation. This dataset contained the time, date, and duration of every load shedding incident since 2007, at a substation level. Based on this dataset, we were able to derive an average availability factor of electricity per month at a substation level for every year since 2007. This availability factor was calculated as the average duration of load shedding in minutes experienced by a particular substation divided by the total number of minutes in a month. We were then able to estimate the magnitude of load shedding in GWh experienced by a substation per month by multiplying the availability factor calculated for a given month by the average electricity sales from that substation for the same month in a non-load shedding year.

Magnitude of load curtailments and power buybacks for top customers not subject to rotational load shedding

Top customers are subject to curtailment and power buybacks as opposed to load shedding, as experienced by other customer segments. The process we followed to estimate the magnitude of these two components of load reduction is illustrated in App Figure 5.

<table>
<thead>
<tr>
<th>Obtained dataset containing incidences of all curtailment events to top customers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obtained electricity sales data which detailed sales to top customers on a half hourly basis</td>
</tr>
<tr>
<td>Added indicators to sales data including hour, week, month and whether curtailment occurred</td>
</tr>
<tr>
<td>Estimated average sales to top customers on an hourly basis without curtailment</td>
</tr>
<tr>
<td>Curtailment magnitude estimated as average sales less actual sales during curtailment events</td>
</tr>
</tbody>
</table>
The starting point for estimating the magnitude of load curtailments was to obtain sales data for all sales to top customers. This sales data was broken down into kWh sold to all top customers nationally on a half-hourly basis for the period 2011-2019 (48 separate data points for each day in the year = 24 hours x 2). Based on this data, we determined that electricity sales to top customers is volatile and fluctuates significantly during the day, with peaks and troughs at certain times.

App Figure 6 illustrates the fluctuation in hourly sales for an average day based on this sales data. Pricing agreements signed with top customers specify time-of-use tariffs, where electricity sales outside of business hours and during off-peak are substantially cheaper than during peak demand times. Sales in MWh to top customers peak during the night and early hours of the morning, and are lowest during times of peak residential demand, such as between 6 am to 10 am, and 5 pm to 9 pm.

Based on descriptive statistics and graphic analysis of the sales data, we found that electricity demand to top customers fluctuates based on the day of the week such that consumption patterns and total demand on a weekday are different to weekends, for example. We discovered that, even for weekdays, there are inter-day fluctuations; on average (i.e. the consumption pattern for an average Monday differs from that of the average Tuesday). Likewise, monthly electricity demand fluctuates. Electricity sales in an average January and an average June are different. Based on these observed variations, we added indicator variables such as day of the week, the hour of the day and month of the year to the sales dataset that allowed us to analyse and segment the data more closely.

After adding indicator variables to the dataset, we obtained another dataset which contained the incidences of all load curtailment events since 2014. This dataset contained the time, date, duration, and stage of all curtailment events. Curtailment agreements signed with key customers specify that
under stage one and two of curtailment, up to 10% of the normal electricity demand should be curtailed. Under level three, this rises to 15%, while stage 4 requires a 20% reduction in demand.

Our estimate of the magnitude of load curtailment considers the hourly, daily, and monthly variation in sales to key customers. We calculated an average consumption for each type of indicator monthly when no curtailment events took place. For example, we calculated the average consumption from 8 am to 9 am on an average Monday in September 2015. We calculated unmet electrical load per incidence of load curtailment as the difference between average demand of key customers in the absence of curtailment (using the detailed averages calculated taking into account the time and date of curtailment and hour of curtailment) and actual electricity sales observed during curtailment.
Appendix B. Review of previous studies on the cost of power outages

B.1. Summary of previous studies on the cost of load shedding in South Africa

Overview and critique of previous studies on the cost of load shedding in South Africa

App Table 1 Summary of the literature on the economic impacts of power shortages in South Africa and the Sub-Saharan African region

<table>
<thead>
<tr>
<th>Author and title</th>
<th>Approach</th>
<th>Description</th>
<th>Critique</th>
</tr>
</thead>
</table>
• In the first scenario, the authors simulate an outage by cutting the capital stock of the electricity sector by 10%. The impact is transmitted through an increase in electricity prices (which reflect increased scarcity). The authors note however that this assumption is unrealistic as Eskom’s tariffs are regulated.  
• In the second set of scenarios, the capital stock of all 40 sectors is cut by 10% to simulate the impact of load shedding on GDP. In the final scenario, the capital stock was cut by varying amounts (2%, 5% or 10%) based on the electricity intensity of each sector.  
• The study found that load shedding cost the economy R4.90/kWh. This was much lower than estimates of the CoUE for infrequent unplanned outages of R75/kWh (PB Power 2008). | • The authors assumed that scheduled load shedding of 3 000 MW, 1 500 MW and 750 MW would be associated with a resultant loss in the capital stock of 10%, 5% and 2%. But the assumption about the amount of capital stock that would be rendered idle by load shedding does not appear to have been calibrated to any historical data and is unsubstantiated.  
• The model does not allow for adaptive resilience or mitigation of the impact of outages – it only simulates the inherent resilience of different sectors to load-shedding incidences. The model does not allow for the possibility of adaptive resilience or mitigation of the impact of outages – it only simulates the inherent resilience of different sectors to load-shedding.  
• The authors try to contrast their CoLS estimates to the cost of running open-cycle gas turbines, but this analysis was flawed since they were unable to relate any of the scenarios modelled to the actual magnitude or frequency of load shedding that would have taken place. |
<table>
<thead>
<tr>
<th>Author and title</th>
<th>Approach</th>
<th>Description</th>
<th>Critique</th>
</tr>
</thead>
</table>
| Goldberg (2015)  | Retrospective Stated-preference survey Revealed-preference survey Case study based on semi-structured interviews | Studied the impact of LS on the retail sector through three alternative methods, 1) semi-structured interviews with retail managers, 2) administering a state-preference or willingness-to-pay survey of retail outlets online and in-store, and 3) collecting financial data from retail head offices on the cost of providing back-up generation (marginal cost method under revealed preference survey method). The authors derived estimates of the CoLS for retailers for different times of the day based on a customer damage function approach. | • The semi-structured interviews insights were based on a small sample (eight interviews), while the sample sizes for the state-preference and revealed preference methods were also fairly limited (106 and 42 respectively).  
• The estimates of the CoLS based on the revealed-preference survey were limited to the cost of running back-up generators and at a total of R716 million and did not include the cost of damages (direct or indirect) but also did not subtract the cost of grid-supplied power that would have been purchased.  
• The stated preference estimates of R13bn for 1H15 likely overestimated the impact on retailers. |
Used Penn World Tables GDP data with satellite-based data on nightlights to arrive at a more accurate measure of economic growth. Data on outages obtained from World Bank’s Enterprise Surveys 2011. Lightning density was used as an instrument for power outages. Results suggest weak power infrastructure is a substantial drag on growth. | Makes use of a very parsimonious model of outages on economic growth – they explain economic growth only in terms of the g (GDP growth per capita), an intercept, the log of outages and an error term.  
In trying to limit the risk of endogeneity by limiting explanatory variables they introduce omitted-variable bias (OVB) – as a result probably attributes too much of the variance in GDP to outages. |
B.2. Review of forward-looking studies focusing on those based on general equilibrium models

Introduction

Wing and Rose note that except for a few case studies of actual events, economy-wide losses associated with both planned and unplanned power outages were typically not analysed until the 1990s. Vinicius Botelho notes that decisions about whether to invest in infrastructure or initiatives to increase power system resilience have been measured mainly in terms of the cost of unplanned outages (either CoUE or VoLL) or output lost in values per kWh of electricity not supplied.

However, the empirical methods most often used to estimate these parameters (partial equilibrium (PE) models, such as input-output tables or social accounting matrices) suffer from several limitations. PE models are limited by their inherent linearity, lack of behavioural content and do not allow for prices to adjust to clear markets.

More specifically, measures of the cost of outages based on partial equilibrium models (e.g. CoUE) rely on the convenient but unjustified assumption that a sector’s output is directly proportional to its electricity consumption and that resources (e.g. capital and labour) are unconstrained. PE models also assume fixed prices (no change in prices or wages in response to demand or supply shocks). Analyses based on PE models cannot account for the fact that interruption costs are time-dependent, although some have proposed adaptations to account for this by applying weighting factors. Lastly, and perhaps most importantly, they do not account for the fact that some industries are more resilient to power outages than others and can adapt – this is particularly relevant when there is a structural electricity supply shortage.

Most of the recent advances in modelling the economic consequences of electricity disruptions are concerned with trying to more accurately reflect the varying ability of consumers to mitigate the losses incurred. As discussed in Section 2.1.3, there are many different tactics that firms employ to cushion themselves against the impact of power outages – some are inherently more resilient (are not very reliant on electricity or can easily outsource the parts of their processes that are) while others can adapt (for example by procuring backup power solutions).

Key features of general equilibrium models

CGE models, as noted by Rose and Wing, maintain the best features of PE models – the high level of sectoral detail and ability to trace linkages between industries – while overcoming many of the limitations of PE models (e.g. fixed prices and unconstrained resources). CGE models are particularly useful for analysing the potential impact of regular planned outages as it is possible to simulate some of the resilience tactics firms are likely to employ. For example, power conservation strategies can be simulated by changing the productivity parameter of a production function, while the inherent resilience of a sector (e.g. ability to substitute inputs and switch to imports) are built into the dynamic equations in the form of substitution elasticities and Armington elasticities (i.e. the elasticity of substitution between products of different countries, a standard assumption of international CGE models), respectively.

Computable general equilibrium (CGE) or dynamic computable general equilibrium models (DCGE) build-up to the macro-economy from microeconomic foundations. CGE models are complete numerical representations of economies in the form of systems of non-linear algebraic equations or related mathematical structures. In contrast to I-O or other PE models, the input-output relations among industries are nonlinear and to a degree flexible, a function of technology assumptions, prices, and other factors. A CGE model consists of:

- A system of nonlinear algebraic equations describing the interaction between micro and macroeconomic variables; and
- A database which takes the form of a social accounting matrix (SAM) and a set of elasticities describing how product substitution takes place.

A SAM model describes the structure of the economy and interlinkages between industries, sectors, households, government, and the rest of the world at a detailed level. The theoretical structure of the typical CGE models are based on neo-classical economic theory: consumers are assumed to maximise utility and firms maximise profits subject to resource constraints.

Advantages and limitations of estimating the impact of electricity supply shortages within a GE framework

Of the 13 studies we found on the economic consequences of persistent electricity shortages, six analyse the potential impacts within a general equilibrium framework. The main advantage of using a static CGE model over the PE models used to estimate the CoUE is that the inherent resilience of a sector - ability to substitute inputs and switch to imports - is built into the dynamic equations of all CGE models in the form of substitution elasticities and Armington elasticities, respectively.

As Wing et. al. note, CGE models overcome the very limiting assumption that economic actors do not engage in substitution (as is the case for measures based on PE models). The analysis by Wing

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71 Wing and Rose, "III. Economic Consequence Analysis of Electric Power Infrastructure Disruptions: An Analytical General Equilibrium Approach."
et al. revealed that when producers and consumers can substitute (e.g. use alternative materials or labour for electricity or imports for domestically produced intermediate inputs) the impact of supply interruptions remain unambiguously negative for the economy but the magnitude of the impact is much smaller.

Of the studies we reviewed, there were four that use a CGE to simulate the impact of outages while allowing for inherent resilience across sectors - these included studies on the economic impacts of power shortages by Major and Drucker\textsuperscript{72} in Hungary, by Ou et al.\textsuperscript{73} in China, Deloitte\textsuperscript{74} in South Africa and Botelho in Brazil.\textsuperscript{75}

All these studies share limitations. In all cases, the electricity shortages were initially simulated by moving the electricity supply curve left - which reduces the quantity of electricity supplied and increases its relative price. However, in all three country cases studied (China, Hungary and South Africa) prices are administered or regulated and there is no perfectly competitive market or 'efficient market mechanism' that would allow prices to rise to reallocate power to its most valuable use. In this regard, analyses based on a CGE framework is likely to underestimate the impact of shortages.

Most of the CGE models used were based on simple Cobb-Douglas production function which has a high degree of substitutability between key inputs to production and consequently also underestimated the true impact of supply shortages. Botelho noted that the general equilibrium properties of rationing policy, other production functions should be tested.

None of these studies attempted to model the ability of firms and households to employ adaptive measures to cushion the impact of outages by either reducing their reliance on electricity or by installing a back-up power supply or generation.

CGE models are theoretical and highly stylised (a model which only tries to reproduce a very specialized time series or economic phenomena) and are therefore quite abstracted from reality. For example, in the Deloitte study, the authors assumed that scheduled load shedding of 3 000 MW, 1 500 MW and 750 MW would be associated with a resultant loss in the capital stock of 10%, 5% and 2%. But the assumption about the amount of capital stock that would be rendered idle by

\textsuperscript{72} Klára Major and Luca Flóra Drucker, \textit{Macroeconomic impact of electric power outage: simulation results from a CGE modelling experiment for Hungary}, EcoMod (2016).

\textsuperscript{73} Peng Ou, Ruting Huang, and Xin Yao, "Economic impacts of power shortage," \textit{Sustainability} 8, no. 7 (2016).

\textsuperscript{74} Deloitte, "Modelling the impacts of electricity disruptions, Chapter 3, Report on Eskom and the Electricity Sector."

\textsuperscript{75} Botelho, "Estimating the economic impacts of power supply interruptions."
a given amount of load shedding does not appear to have been calibrated to any historical data or outage event.

Because CGEs are abstract, theoretical, and comparative they cannot be used to assess the actual historical impact of load shedding on the economy or a particular sector. However, as Botelho notes, GE models do provide a sound theoretical and empirical basis to evaluate the relative economic impacts of different power rationing policies – concerning both intensity and design.

Some of the more recent studies including Rose et al. and Wing et al. have shown how CGE models can be extended to evaluate the ability of firms to mitigate against or adapt to regular electricity shortages. In the most ‘realistic’ of the three scenarios modelled, Wing et al., extend their CGE models to allow firms to make for deliberate investments in mitigation (back-up generation) to further dampen the consequent price and quantity changes, and ultimate welfare losses. However, they found that because of the complexity of the algebraic equations the results were hard to interpret, and they had to rely on the fairly crude assumption that all industries employ a single monolithic backup technology.

In conclusion, GE models, because they are highly disaggregated (often including detail on between 20 and 100 different sectors in the economy and the linkages between them) provide a useful theoretical framework to assess the potential impact of various power rationing policies or events on different sectors.

They can also be used to provide more accurate estimates of the cost of electricity shortages (particularly regular planned outages) than traditional measures based on PE models (such as CoUE and VoLL). This is because they overcome many of the limiting or unrealistic assumptions that PE models are based on – they allow for prices to adjust, place a constraint on resources and allow for substitution between inputs (e.g. capital and labour) and local production and imports.
App Table 2 Summary studies based on forward-looking approaches to simulating the impact of electricity shortages

<table>
<thead>
<tr>
<th>Author and title</th>
<th>Approach</th>
<th>Description</th>
<th>Critique</th>
</tr>
</thead>
<tbody>
<tr>
<td>Major, Klára, and Luca Flóra Drucker. (2016)</td>
<td>General equilibrium model</td>
<td>- Presents the results of a CGE that is used to assess how an electricity supply shock might influence the Hungarian economy.</td>
<td>- The CGE assumes perfectly competitive markets so that the adjustment is driven by mainly by rising electricity prices.</td>
</tr>
<tr>
<td>Macroeconomic Impact of Electric Power Outage:</td>
<td></td>
<td>- The electricity outages are modelled by the decrease in the supply of energy. The capital stock in the energy industry is shocked, which leads to a decrease in the supply of energy.</td>
<td>- In the base case, when prices are flexible and there are no limits to adjustments, agents with the highest motivation to do so react more: either because their price-elasticity is higher or because their energy intensity is higher or because they still need to compete with foreign competitors.</td>
</tr>
<tr>
<td>Simulation Results from a CGE Modelling Experiment</td>
<td></td>
<td>- In the base scenario, a ~2% decline in the supply of energy leads to a 0.53% decline in the GDP.</td>
<td>- Therefore, this estimation must be considered as a lower bound on actual costs of electricity outages: if there are limitations to adjustments of any kind, the GDP costs of the outage can be even higher.</td>
</tr>
<tr>
<td>for Hungary.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ou, Peng, Ruting Huang, and Xin Yao (2016). Economic Impacts of Power Shortage. in China</td>
<td>General equilibrium model</td>
<td>- A static CGE model is used to simulate the economic impacts of hard power shortage and soft power shortage. Simulation results show that the negative effects of power shortage on economic development are very significant, and the effects vary across sectors. The study simulates the impact of four shortage scenarios - a: 3%, 7%, 11% and 15% reduction in the power supply.</td>
<td>- The power shortages are simulated by moving the electricity supply curve left (reducing the quantity of electricity supplied and increasing the price). In reality, electricity prices in China are administered and cannot adjust so the rising prices as an ‘efficient market mechanism’ to reallocate power is an unlikely scenario and in reality, the impact of shortages would likely be greater than reported.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- The results suggest that in the scenario of hard power shortage, the industrial sector suffers most. The economic cost of power shortage is considerable, and the study notes the main reason for it is the specific administrative pricing system that applies to electricity in China. There is little doubt that the cost of avoiding the shortage is less than the cost of the power shortages.</td>
<td>- On the other hand, the study does not appear to have incorporated the possibility of adaptative responses such as mitigation (e.g. back-up power).</td>
</tr>
<tr>
<td>Author and title</td>
<td>Approach</td>
<td>Description</td>
<td>Critique</td>
</tr>
<tr>
<td>---------------------------------------------------------------------------------</td>
<td>-----------------------------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Botelho, Vinicius. (2019). Estimating the Economic Impacts of Power Supply Interruptions. Energy Economics.</td>
<td>General equilibrium model</td>
<td>• This paper notes that the costs of power system rationing are usually estimated using reduced form linear models or I-O analysis that are ill-suited to understanding how consumers respond to shortages or rationing policies. This paper reviews alternative approaches to estimating the effects of power system rationing and concludes that GE models are best suited to evaluate the effects of different power-rationing strategies. The paper concludes that general equilibrium models provide theoretical and empirical bases to estimate the economic impacts of rationing policies – both rationing intensity and design.</td>
<td>• One of the limitations of the study is that CGE is based on a Cobb-Douglas production function which high-degree of substitutability between inputs probably underestimated the true rationing impact values. The general equilibrium properties of rationing policy, other production functions must be tested.</td>
</tr>
<tr>
<td>Rose, Liao, Oladosu. 2007. Business Interruption Impact of a Terrorist Attack on the Electric Power System of Los Angeles: Customer Resilience to a Total Blackout</td>
<td>General equilibrium model</td>
<td>• The study estimates economic losses from electricity interruptions for businesses from a terrorist attack in Los Angeles. Indirect effects and resilience are also included in the losses estimate. Indirect effects (multiplier/GE effects) and resilience are included in the losses estimate. They find moderate indirect effects, but strong resilience, that pushes in the opposite direction, indicating that customers can mute the potential shock to their business operations by as much as 86%. • They find that the most prominent resilience measure is the rescheduling (recapture) of production after electric service is restored. This, together with inherent aspects of the electricity-economy relationship (e.g. inter-fuel substitution) and adaptive responses (e.g. conservation, on-site generation) can reduce the potential disruption impacts significantly.</td>
<td>• The study is limited to assessing the economic impacts of an electric power outage on businesses. • The study states that several considerations are omitted, such as the value of any lives lost, increased crime, psychological trauma, some infrastructure costs, and property damage. • The authors acknowledge that many of the resilience factors are rough estimates and that more empirical work is needed to refine them.</td>
</tr>
<tr>
<td>Wing, Sue, and Rose. (2019) Economic Consequence Analysis of Electric Power Infrastructure Disruptions: An Analytical General Equilibrium Approach.</td>
<td>General equilibrium model</td>
<td>• The authors developed a simple analytical general equilibrium model of the economy-wide impacts of electricity infrastructure disruptions. The authors modelled three scenarios – in the first they consider the extreme case where economic actors do not engage in substitution (as is the case in studies based on PE models).</td>
<td>• The study is limited by the stylised, highly simplified nature of GE models. It is not consistent with the physical reality of the power system and additional research would be required to align the model with the reality of the power sector. • This was particularly relevant for the scenario where they allowed substitution and back-up because they relied on a rather crude assumption that all industries employ a single monolithic backup technology.</td>
</tr>
<tr>
<td>Author and title</td>
<td>Approach</td>
<td>Description</td>
<td>Critique</td>
</tr>
<tr>
<td>--------------------------------------------------------------------------------</td>
<td>--------------------------------------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Greenberg, Mantell, Lahr, Felder, Zimmerman. (2007)</td>
<td>Structural econometric time series model and I-O model</td>
<td>• The economic impacts of potential terrorist attacks on the New Jersey electric power system are examined using a regional econometric model.</td>
<td>• The authors state that a weakness of the model is that the set of important relationships among sectors, as well as their magnitudes and directions, are fixed. It is unknown how relationships among sectors change when one or more of them suffers a large, unexpected shock.</td>
</tr>
<tr>
<td>Short and intermediate economic impacts of a terrorist-initiated loss of electric power: A case study of New Jersey</td>
<td></td>
<td>• The study finds that the magnitude and duration of the effects vary by type of business and income measure.</td>
<td>• The authors also acknowledge that the model cannot directly capture the immediate reactions to economic shocks of business, government, and consumers.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• The suggested policy implication is that the cost and benefits of making the electric power system more resilient to plausible attacks should be weighed and that the restorative capacity of the system should be strengthened.</td>
<td>• Most importantly, the authors state that no simulation model can perfectly forecast the implications of a shock.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• The accuracy of the results is subject to limited information and data.</td>
</tr>
</tbody>
</table>
B.3. Review of retrospective studies with a focus on econometric methods

Introduction

Of the 13 studies we reviewed, four were based on an econometric analysis of the cost of historical electricity supply shortages. Fisher-Vanden, Mansur and Wang\textsuperscript{76} and Allcot et al.\textsuperscript{77} estimated the impact of electricity shortages based on panel data for manufacturing firms in China and India respectively (App Table 3). Andersen, and Dalgaard\textsuperscript{78}, as discussed earlier, estimated the impact of electricity shortages across Sub-Saharan Africa using time series techniques, while Ellahi\textsuperscript{79} estimates the impact of electricity supply constraints on the development of the industrial sector in Pakistan using an ARDL model (App Table 3).

Key features of econometric models

Econometrics can be defined as the social science in which the tools of economic theory, mathematics, and statistical inference are applied to the analysis of economic phenomena.\textsuperscript{80} The econometric analysis of the cost of electricity supply interruptions is usually based on one of two types of data – times series data or pooled and panel data. A time series is a set of observations on the values that a variable such as GDP takes at different points in time – usually collected at regular intervals (monthly, quarterly, annually). Pooled data sets are multi-dimensional in that they contain values for different attributes of several firms or countries collected over time. Panel data sets are simply a special type of pooled data in which the same cross-sectional unit (e.g. firm) is surveyed over time.

Advantages and limitations of the econometric approach to estimating the historical impact of electricity supply shortages

One of the main advantages of studies based on econometric analysis of historical time series or panel data is that, in contrast to highly stylised and theoretical GE models, the results are based on the empirical analysis of real-world outage events. Studies based on econometric analysis typically aim to isolate the marginal impact of a particular load shedding event (or series of events) on economic growth or industry-level production. In this sense, they can be used to produce estimates of the actual historical economic costs (direct and indirect and net of adaptive response) of regular or persistent power shortages. For example, Andersen and Dalgaard\textsuperscript{81} estimated across a sample of 39 Sub-Saharan African countries that a one per cent increase in the number of outages reduced long-run GDP per capita by 2.86 per cent during the period 1997 to 2007. It is possible however

\textsuperscript{76}Fisher-Vanden, Mansur, and Wang, “Electricity shortages and firm productivity: evidence from China’s industrial firms.”
\textsuperscript{77}Allcott, Collard-Wexler, and O’Connell, “How do electricity shortages affect industry? Evidence from India.”
\textsuperscript{78}Andersen and Dalgaard, “Power outages and economic growth in Africa.”
\textsuperscript{79}Ellahi, “Testing the relationship between electricity supply, development of industrial sector and economic growth: An empirical analysis using time series data for Pakistan.”
\textsuperscript{81}Andersen and Dalgaard, “Power outages and economic growth in Africa.”
that they overestimated the impact of outages on GDP per capita, by failing to adequately control for other influences.

One of the limitations of econometric analyses is that it can be difficult to accurately isolate the impact of load shedding (particularly if it is a one-off event) on economic growth from other influences. One of the challenges in this regard, endogeneity. Power outages are likely correlated with a number of the other determinants of economic growth (e.g. growth in gross fixed capital formation) and are subject to reverse-causal influence (economic growth also causes shortages). To address the potential endogeneity of shortages a proper identification strategy is required. Anderson and Dalgaard\textsuperscript{82} instrument for shortages by using lightning density as an exogenous determinant of power disturbances. Lightning damage accounts for about 65% of all over-voltage damage to electrical distribution networks in South Africa. Allcot et al.\textsuperscript{83} instrument with changes in electricity production from dams, which are driven by changes in the amount of water flowing into reservoirs.

Econometric analysis is also frequently limited by the relatively low frequency of macroeconomic data (quarterly or annual), quality of data on electricity outages and the length of the economic time series – the introduction of several lags of each explanatory variable for example in a Vector Autoregressive (VAR) or Vector Error Correction Model (VECM) model can consume a lot of degrees of freedom.

Another advantage of retrospective econometric studies it that is possible to estimate the net impact of power shortages on different groups or sectors - to understand which firms or sectors are more resilient (able to avoid or cushion the impact) than others. For example, Allcott et al.\textsuperscript{84} found that in 2005 when Indian manufacturing firms faced outages, 7.1% of the time, that the output of firms that were able to self-generate (i.e. had back-up generators) lost only 0.7% of their output. Firms that did not have back-up generation lost 10.3% of their output. The authors concluded that electricity shortages were a substantial drag on Indian manufacturing from 1992 to 2010, reducing manufacturing output by an average of about five per cent over the period.

\textsuperscript{82} Andersen and Dalgaard, "Power outages and economic growth in Africa."

\textsuperscript{83} Allcott, Collard-Wexler, and O’Connell, "How do electricity shortages affect industry? Evidence from India."

\textsuperscript{84} Allcott, Collard-Wexler, and O’Connell, "How do electricity shortages affect industry? Evidence from India."
## App Table 3 Summary of international studies that estimate the historical impact of power shortages (retrospective approach)

<table>
<thead>
<tr>
<th>Author and title</th>
<th>Approach</th>
<th>Description</th>
<th>Critique</th>
</tr>
</thead>
</table>
• The study found that in response to electricity scarcity, Chinese firms substitute materials for energy – buying rather than making intermediate inputs to production (i.e. outsourcing). This enabled firms to minimise productivity losses.  
• Even the less energy-intensive industries, like food and machinery, increased materials share and reduced shares of electricity. The study did not find evidence that electricity shortages led to a marked increase in self-generation – there was some evidence in mining, food, and petroleum, but even so, less than 20% of firms opted to self-generate. As a result of the increase in electricity scarcity unit production costs rose by 8%. | • The study was limited to studying the effects of electricity scarcity on energy-intensive manufacturing firms.  
• The study does not examine the effect of power shortages on investment and employment by industrial firms. |
• The study found the cost of an unsupplied kWh of electricity is significantly higher than the cost of electricity from the public grid. Lastly, they found that the cost of mitigating a kWh of electricity is significantly higher than a cost-reflective tariff would have been.  
• Firms engaging in exports, and those using the Internet for their operation suffered higher unmitigated outage costs despite having a higher propensity of investing in a back-up generation. Unmitigated costs or damages still account for the larger proportion of the total outage costs despite the high prevalence of backup ownership among the firms. | • The study (like most others) does not illustrate the broader and longer-term impacts of power shortages on investment and employment.  
• It also did not estimate the potential environmental costs associated with back-up power (e.g. noise and emissions from diesel back-up generators).  
• Finally, the conversion of the reported electricity expenditure by firms to obtain their corresponding electricity demand by dividing it by an approximate price may not be accurate. |
<table>
<thead>
<tr>
<th>Author and title</th>
<th>Approach</th>
<th>Description</th>
<th>Critique</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hunt, Collard-Wexler, and O’Connell (2016) How Do Electricity Shortages Affect Industry? Evidence from India.</td>
<td>Econometric analysis of pooled data. Case study</td>
<td><em>Developed a hybrid Leontief and Cobb-Douglas production function model that characterises how input shortages affect firms (2013). In the case study, they analysed how ‘power holidays’ affect daily production at large Indian textile plants, using data from Bloom et al.</em>&lt;br&gt;<em>Studied the short-run effects of electricity shortages on all Indian manufacturing plants between 1992 and 2010, using archival data on shortages, panel data, and an instrument for shortages based on variation in hydro reservoir inflows. Found that electricity shortages were a substantial drag on Indian manufacturing, reducing output by about five per cent. Found that because of economies of scale in self-generation, shortages impose much greater losses on small plants.</em></td>
<td><em>The results are based on a static model, focusing on the effects of annual variation in shortages with fixed capital stock. However, because most of the policies available to address shortages would be unlikely to fully eliminate shortages for many years, a model with annual variation may identify the most policy-relevant effects.</em></td>
</tr>
<tr>
<td>Ellahi (2013) Testing the relationship between electricity supply, development of industrial sector and economic growth: An empirical analysis using time series data for Pakistan</td>
<td>Econometric times series analysis</td>
<td><em>The empirical analysis is based on Romer’s endogenous growth theory and uses an Auto-Regressive Distributed Lag (ARDL) model, using data for Pakistan from 1980-2009.</em>&lt;br&gt;<em>The author finds that electricity shortages in Pakistan have a significant negative short-run and long-run effect on the performance of the industrial sector. They find that electricity is a significant contributing factor to long-run economic growth.</em></td>
<td><em>The regression model used in this study is subject to a number of shortcomings. Firstly, it only includes a simple binary dummy variable for the periods with and without electricity shortages, without capturing any information on the frequency or magnitude of the outages. Further, the regression includes variables for both outages and electricity consumption, two variables that almost certainly correlated.</em>&lt;br&gt;<em>Furthermore, it appears the model was poorly specified and has low explanatory power as none of the estimated coefficients in either the error-correction or long-run from of the ARDL model (on outages or other determinants of growth) were statistically significant – the p-values were all very high.</em>&lt;br&gt;<em>The study also produces a seemingly counterintuitive negative relationship between labour and growth, which further detracts from confidence in the results.</em></td>
</tr>
</tbody>
</table>
Appendix C. Energy-augmented production function

In this section, we describe the panel regression which provided the alternative estimate on the cost of load shedding and provides technical detail on the data inputs and methods used. Our panel regression is based on the Cobb-Douglas production function, a positive nonconstant function that expresses economic output as a function of capital, labour and total factor productivity. The production function is a key concept in mainstream neoclassical economics.\(^{85}\) Almost all economic theories presuppose a production function, either on the firm level or the aggregate level.

The panel regression was estimated pooled classic linear regression model with fixed effects, where the fixed effects control for the different industries. We structure the components of the production function as matrices (by sector, at one-digit SIC level). The agriculture and utilities industries are, however, excluded from the panel production function regression, as the Cobb-Douglas specification is not a good predictor for their GDP output.

The coefficients on the variables yielded sensible results (App Figure 7 and App Table 4). When we included electricity sales as an input variable, the coefficient on capital reduced. This was expected, as electricity consumption is positively correlated with capital stock formation - the more equipment, buildings, machinery, the more electricity is consumed.

We estimated how much growth in electricity sales have contributed to growth in GDP over the last ~17 years (2003 to 2019) and found that a 1% increase in electricity sales was associated with a 0.15% increase in GDP after controlling for the influence of capital, labour, and technology. Thereafter, we estimated the percentage point change in GDP growth that could have been attributed load shedding in each of the quarters when load shedding occurred. This was done by multiplying the coefficient of 0.15 by the percentage of electricity sales lost due to load shedding. We inferred amount of GDP lost during load shedding by multiplying by the amount of GDP generated in each of the 16 quarters and dividing by the magnitude of load shedding in GWh and inflated these costs to 2020 prices.

\(^{85}\) Wang and Fu, “Some Characteristics of the Cobb-Douglas and CES Production Functions in Microeconomics.”
App Figure 7 Relationship between GDP, capital and labour for each industry

Legend: 1 = Agri; 2 = Mining; 3 = Manufacturing; 4 = Utilities; 5 = Construction; 6 = Trade; 7 = Transport; 8 = Business; 9 = Personal; 10 = Government
### App Table 4 Panel regression output

Dependent Variable: LOG(GDP_EXCL_AGRI_UTIL)
Method: Panel Least Squares
Date: 08/03/20 Time: 13:56
Sample (adjusted): 2003Q1 2019Q4
Periods included: 68
Cross-sections included: 8
Total panel (balanced) observations: 544

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.239637</td>
<td>0.229806</td>
<td>-1.042780</td>
<td>0.2975</td>
</tr>
<tr>
<td>LOG(OPENING CAPITAL_SMOOTHED)</td>
<td>0.235433</td>
<td>0.023198</td>
<td>10.14879</td>
<td>0.0000</td>
</tr>
<tr>
<td>LOG(LABOUR_PALMS)</td>
<td>0.469995</td>
<td>0.021258</td>
<td>22.10881</td>
<td>0.0000</td>
</tr>
<tr>
<td>LOG(SALES)</td>
<td>0.149549</td>
<td>0.012205</td>
<td>12.25307</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

**Effects Specification**

Cross-section fixed (dummy variables)

<table>
<thead>
<tr>
<th>Root MSE</th>
<th>0.053745</th>
<th>R-squared</th>
<th>0.991130</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean dependent var</td>
<td>12.46813</td>
<td>Adjusted R-squared</td>
<td>0.990964</td>
</tr>
<tr>
<td>S.D. dependent var</td>
<td>0.571191</td>
<td>S.E. of regression</td>
<td>0.054297</td>
</tr>
<tr>
<td>Akaike info criterion</td>
<td>-2.968682</td>
<td>Sum squared resid</td>
<td>1.571372</td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>-2.881755</td>
<td>Log likelihood</td>
<td>818.4815</td>
</tr>
<tr>
<td>Hannan-Quinn criter.</td>
<td>-2.934696</td>
<td>F-statistic</td>
<td>5955.817</td>
</tr>
<tr>
<td>Durbin-Watson stat</td>
<td>0.187126</td>
<td>Prob(F-statistic)</td>
<td>0.000000</td>
</tr>
</tbody>
</table>
C.1. The method used to derive the quarterly capital stock series

Annual fixed capital stock by industry is published by the SARB. Until 2016, the SARB also published a quarterly series of gross fixed capital formation for six sectors including mining and manufacturing. We sourced the discontinued series from the SARB and interpolated annual series to generate quarterly data for the remainder of the period (2016 to 2019). Following the method used by Burger et al.86 the quarterly fixed capital formation by industry is used to calculate the quarterly capital stock by simultaneously solving the equations below for capital stock $k_{t,q}$ in quarter $q$ of year $t$. $K_t$ and $K_{t-1}$ are the gross fixed capital stock values reported at the end of year $t$, while $I_{t,q}$ is the gross fixed capital formation for the quarter $q$ in year $t$. The solution of these equations also allows for quarterly depreciation, $d$, to be identified per industry. The depreciation rates can then be used to construct a quarterly capital series.

$$k_{t,1} = (1 - d)K_{t-1} + I_{t,1}$$
$$k_{t,2} = (1 - d)k_{t,1} + I_{t,2}$$
$$k_{t,3} = (1 - d)k_{t,2} + I_{t,3}$$
$$K_t = (1 - d)k_{t,3} + I_{t,4}$$

C.2. The method used to derive the quarterly series on electricity sales by sector

Data on electricity sales were sourced from Eskom. Three different sources of sales data were used to derive monthly series of electricity sales for each of the ten industries reported by Standard Industrial Classification (SIC) code at the 2-digit level in the national accounts, these include:

8. Highly disaggregated electricity sales and revenue data classified in most cases at the 5-digit SIC code) for each of Eskom’s 6 regions and its top customers, extracted from the billing system at Eskom distribution for the years 2006 to 2019.

9. Highly disaggregated national sales and revenue data (classified in most cases at the 5-digit SIC code) sourced from Eskom distribution for the years 2003 to 2008.

10. Aggregated total monthly national sales data by major Eskom customer category, extracted from SAP system at Eskom distribution from 2006 to 2019.

Eskom does not report electricity sales and revenue by at the SIC 2-digit level, which is how GDP data is aggregated in the South African System of National Accounts. Eskom distribution does classify its direct sales to commercial and industrial customers by 5-digit SIC codes in the billing system but these are then aggregated into the following 13 Eskom customer categories which do not map in most cases to the SNA (System of National Accounts):

11. Independent Power Producers

86 Frierich Kreuser, Rulof Burger and Neil Rankin, The elasticity of substitution and labour-displacing technical change in post-apartheid South Africa.

Nova Economics Appendix C 82
The process that we followed to categorise Eskom’s highly disaggregated electricity sales into industries at the 2-digit SIC level is as follows:

i. We began by mapping the highly disaggregated monthly sales and revenue, recorded by region and in some cases by 5-digit SIC code to the 10 industries at 2-digit SIC level, as reported in the national accounts using the categorisation presented in App Table 5.

ii. Some categories of sales could not be mapped to the SIC industries. These included various residential sales, international and bulk sales, and sales to re-distributors (Local municipalities and major metropolitan areas). In doing so we had to account for missing values and negative sales values (which were included) because they are corrections of prior billing errors.

iii. Eskom records these sales by “Eskom region”, six are defined by geographic boundaries and the seventh consists of the utility’s top customers – the regions are Central, Eastern, Northern, North West, Southern, Western, and top customers. The regional data classified by the ten industries and four additional customer categories were summed to create a 14 separate national series of monthly sales and revenue.

iv. We compared these series where possible with Eskom’s aggregates and found that there was an issue with the residential electricity sales series in Eskom’s billing system and so we replaced this series with data from Eskom’s SAP system.

v. The Eskom sales and revenue data captured in the current billing and SAP systems only dates back to 2006 but for the econometric analysis, we needed a longer time series. Fortunately, we were able to obtain a previous set of data on national monthly electricity sales and revenue at a similar level of disaggregation (classified in most cases at the 5-digit SIC code) from Eskom distribution for the years 2003 to 2008.

vi. We repeated the mapping exercise for 2003 to 2008 sales data using the classification in Appendix F and then combined these to create national time series of electricity sales for ten industries in the SNA and four additional sectors spanning the period 2003 to 2019.

12. Agricultural
13. Re-distributors
14. Commercial
15. Industrial
16. International Sales
17. Mining
18. Prepayment
19. Public lights
20. Residential
21. Traction
22. External Sales
23. Internal Sales
vii. The final challenge in the process was how to allocate the almost 40% of Eskom’s total direct electricity sales that are sold to municipal redistributors to the various industries that are the end-consumers but buy Eskom power via municipalities.

viii. To allocate municipal sales to the relevant industries that consumed them we used the breakdown of municipal electricity sales by industry provided in the State of Cities report for 2006, 2011 and 2014/15 and additional data provided by the authors of Eskom’s CoUE report for the 2014/15 year. The reports cover sales by 13 of South Africa’s largest metropolitan and local municipalities.

ix. Since we only had a breakdown of municipal sales by the industry for three of the 17 years between 2003 and 2019, we interpolated the trend in the composition of sales for the intervening periods.

x. We then summed Eskom’s direct sales and reallocated municipal sales by industry to create ten series reflecting Eskom’s monthly sales by industry (at the 2-digit level) but this excludes international sales and residential sales.

**App Table 5 Mapping Eskom sales to 2-digit SIC classification of industries**

<table>
<thead>
<tr>
<th>SIC category (high-level)</th>
<th>Allocation by Eskom codes</th>
<th>New SIC codes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, Forestry and Fishing</td>
<td>1</td>
<td>01 to 03</td>
</tr>
<tr>
<td>Mining and Quarrying</td>
<td>2</td>
<td>05 to 09</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>3</td>
<td>10 to 33</td>
</tr>
<tr>
<td>Electricity, Gas and Water</td>
<td>412, 413, 420, 41111, 41113, 4SPU</td>
<td>35 to 39</td>
</tr>
<tr>
<td>Construction</td>
<td>5</td>
<td>41 to 43</td>
</tr>
<tr>
<td>Wholesale and Retail Trade, Hotels and Restaurants</td>
<td>6</td>
<td>45 to 47</td>
</tr>
<tr>
<td>Transport, Storage and Communication</td>
<td>7</td>
<td>49 to 63</td>
</tr>
<tr>
<td>Finance, Real Estate and Business Services</td>
<td>8, 5SPU Commercial</td>
<td>64 to 82</td>
</tr>
<tr>
<td>General Government Services</td>
<td>91, 4publiclighting</td>
<td>84</td>
</tr>
<tr>
<td>Personal Services</td>
<td>92 to 99</td>
<td>85 to 99</td>
</tr>
<tr>
<td>Redistributors</td>
<td>41112</td>
<td>0SPU Residential, 0SPU Prepayment, 01010-Urban Domestic, 01020-Rural Domestic, 01040-Peri-Urban Domestic</td>
</tr>
<tr>
<td>Residential</td>
<td></td>
<td></td>
</tr>
<tr>
<td>International</td>
<td>41114</td>
<td>41116</td>
</tr>
<tr>
<td>Bulk supplies</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
## Appendix D. Expenditure side regression output

**App Table 6 Classic linear regression model estimates (2003Q1-2019Q4)**

<table>
<thead>
<tr>
<th></th>
<th>Manu.</th>
<th>Retail sales</th>
<th>Transport</th>
<th>Utilities</th>
<th>Personal</th>
<th>Agri</th>
<th>Mining</th>
<th>Constrn.</th>
<th>Finance</th>
<th>Govt.</th>
<th>Total GDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.523269* (0.224299)</td>
<td>0.051437- (0.113183)</td>
<td>0.494876*** (0.117793)</td>
<td>-0.063304- (0.197326)</td>
<td>0.94773- (0.114995)</td>
<td>-0.017698- (0.332945)</td>
<td>0.394786- (0.639073)</td>
<td>0.337557- (0.261984)</td>
<td>0.481112*** (0.107877)</td>
<td>0.43392*** (0.09286)</td>
<td>0.235226** (0.094041)</td>
</tr>
<tr>
<td>LS_GWH_PC_sales</td>
<td>-0.189244 P. 0.1384 (0.597257)</td>
<td>-0.314774 P. 0.1683 (0.225958)</td>
<td>-0.8458*** (0.2333)</td>
<td>-0.201381*** (0.060718)</td>
<td>-0.0 P. 0.945 (0.203605)</td>
<td>-1.671265 P. 0.0622 (0.880134)</td>
<td>-0.933103 - (1.139481)</td>
<td>-0.677822 P. 0.1976 (0.520646)</td>
<td>-0.013 P. 0.9509 (0.211459)</td>
<td>-0.131501 P. 0.4778 (0.184134)</td>
<td>-0.388425 P. 0.0248 (0.169019)</td>
</tr>
<tr>
<td>@PC(FCE) (Final Consumption Expenditure)</td>
<td>0.857712*** (0.107671)</td>
<td>0.055798- (0.065512)</td>
<td>0.094237** (0.031362)</td>
<td>0.465339*** (0.114435)</td>
<td>0.187551** (0.068372)</td>
<td>0.139543*** (0.028296)</td>
<td>0.090173*** (0.024856)</td>
<td>0.099911*** (0.023029)</td>
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</tr>
<tr>
<td>@PC(KBP6009D_GFCF) (Gross Fixed Capital Formation)</td>
<td>0.085613* (0.079620)</td>
<td>0.15908- (0.115928)</td>
<td>0.166866- (0.09639)</td>
<td>-1.06692* (0.519746)</td>
<td>0.837519** (0.247345)</td>
<td>0.308122** (0.100562)</td>
<td>0.186421* (0.088686)</td>
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<tr>
<td>@PC(KBP6008D_FCEG) (FCE Govt.)</td>
<td>0.500258* (0.060718)</td>
<td>0.396386*** (0.097992)</td>
<td>0.692995- (0.429689)</td>
<td>-0.002141* (0.000919)</td>
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<tr>
<td>@PC(KBP6007D_FCEH) (FCE Households)</td>
<td>0.15908- (0.115928)</td>
<td>0.166866- (0.09639)</td>
<td>0.819876* (0.807396)</td>
<td>-0.056416** (0.020525)</td>
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<tr>
<td>Dummy 2008/09 (Financial crisis dummy)</td>
<td>-4.16851*** (0.840064)</td>
<td>-0.62303* (0.314098)</td>
<td>0.481256* (0.247164)</td>
<td>-0.595136** (0.22963)</td>
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<tr>
<td>Dummy Oil Price</td>
<td>1.141546*** (0.314508)</td>
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<tr>
<td>Dummy Rain</td>
<td>8.819864*** (1.147744)</td>
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<tr>
<td>Dummy Drought</td>
<td>-8.414656*** (1.159585)</td>
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<tr>
<td>Dummy Credit Boom</td>
<td>1.568894*** (0.279152)</td>
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</tr>
<tr>
<td>R2</td>
<td>0.4091</td>
<td>0.546975</td>
<td>0.53939</td>
<td>0.395272</td>
<td>0.440478</td>
<td>0.718645</td>
<td>0.100717</td>
<td>0.307327</td>
<td>0.581595</td>
<td>0.302363</td>
<td>0.67734</td>
</tr>
<tr>
<td>N</td>
<td>68</td>
<td>68</td>
<td>68</td>
<td>68</td>
<td>68</td>
<td>68</td>
<td>68</td>
<td>68</td>
<td>68</td>
<td>68</td>
<td>68</td>
</tr>
</tbody>
</table>

Note: *** p<0.001, **p<0.01, *p<0.05, - p>0.05 (not significant); standard errors in parentheses
### App Table 7 ARDL regression estimates (2003Q1-2019Q4)

<table>
<thead>
<tr>
<th>Selected model (lags in dynamic regressors)</th>
<th>Manu.</th>
<th>Retail sales</th>
<th>Transport</th>
<th>Utilities</th>
<th>Personal</th>
<th>Agri.</th>
<th>Mining</th>
<th>Constrn.</th>
<th>Finance</th>
<th>Govt.</th>
<th>Total GDP</th>
</tr>
</thead>
</table>

#### Selected variables of interests:

| LOG(GDP(-1)) | 0.534063*** | (0.092118) | 0.833977*** | (0.076777) | 1.161302*** | (0.10666) | 0.76037*** | (0.11666) | 1.198837*** | (0.108366) | 1.142966*** | (0.068232) | 0.32944*** | (0.03058) | 0.845908*** | (0.029611) | 0.828885*** | (0.033092) | 0.786639*** | (0.075328) |
| LOG(GDP(-2)) | 0.24494** | (0.111716) | 0.015982** | (0.140204) | -0.496085*** | (0.096726) | -0.262934** | (0.066821) |
| LOG(GDP(-3)) | 0.172375 | (0.111795) |
| Constant | 1.7186*** | (0.402874) | 0.074063 | (0.111396) | 0.277113** | (0.112042) | 0.551607 | (0.416624) | 0.177988 - (0.17506) | 0.39239 - (0.278261) | 9.986889*** | (1.685167) | 0.114948 - (0.281963) | -0.379026** | (0.071121) | 0.035769 - (0.230412) | 0.859376** |

#### Fixed regressors:

| LS_GWH_PC_sales (Load shedding as a % of sales) | -0.01044** | (0.005225) | -0.004061 | (0.002226) | -0.00722** | (0.00252) | -0.010663 | P. 0.00155 | 0.008452 | (0.008087) | 0.0001672 | P. 0.00046 | 0.000944 | P. 0.003206 | 0.00057 | P. 0.007883 | (0.00214) | -0.0000108 | P. 0.003743 | -0.002572 | P. 0.00163 |
| Dummy 2008/09 (Financial crisis) | -0.05103*** | (0.009423) | -0.007693** | (0.003386) | -0.005452 - (0.004025) | -0.013651** | (0.007703) | -0.01638** | (0.005134) | -0.000771 - (0.00336) | 0.00438 - (0.002766) | -0.009724** | (0.002857) |
| Dummy Drought | -0.081022*** | (0.010529) |
| Dummy Rains | 0.068087*** | (0.011559) |
| Dummy Oil Price | 0.010459** | (0.003766) |

| R2 | 0.982626 | 0.998624 | 0.998802 | 0.960811 | 0.999222 | 0.975834 | 0.755778 | 0.99911 | 0.999187 | 0.99933 | 0.999156 |
| N | 68 | 68 | 68 | 68 | 68 | 68 | 68 | 68 | 68 | 68 | 68 |

Note: *** p<0.001, **p<0.01, - p>0.05 (not significant); standard errors in parentheses
Appendix E. Impact of load shedding on GDP growth by sector

**App Figure 8** Impact of load shedding on agriculture sector GDP growth

![Graph showing the impact of load shedding on agriculture sector GDP growth.](image)

- Decline in GDP attributed to LS
- GDP Agri
- GDP growth in the absence of LS

**App Figure 9** Impact of load shedding on manufacturing sector GDP growth

![Graph showing the impact of load shedding on manufacturing sector GDP growth.](image)

- Decline in GDP attributed to LS
- GDP Manu.
- GDP growth in the absence of LS
App Figure 10 Impact of load shedding on utilities sector GDP growth

App Figure 11 Impact of load shedding on construction sector GDP growth
**App Figure 12** Impact of load shedding on retail sector GDP growth

**App Figure 13** Impact of load shedding on transport sector GDP growth
App Figure 14 Impact of load shedding on finance sector GDP growth

App Figure 15 Impact of load shedding on government sector GDP growth
App Figure 16 Impact of load shedding on personal services sector GDP growth

![Graph showing the impact of load shedding on personal services sector GDP growth from 2003 to 2019. The graph illustrates the decline in GDP attributed to load shedding and the personal GDP growth in the absence of load shedding.](image-url)
## Appendix F. Industry classification by SIC code

### App Table 8 Industry classification by SIC code

<table>
<thead>
<tr>
<th>SIC</th>
<th>Short name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIC 1</td>
<td>Agri.</td>
<td>Agriculture, hunting, forestry, and fishing</td>
</tr>
<tr>
<td>SIC 2</td>
<td>Mining</td>
<td>Mining and quarrying</td>
</tr>
<tr>
<td>SIC 3</td>
<td>Manu.</td>
<td>Manufacturing</td>
</tr>
<tr>
<td>SIC 4</td>
<td>Utilities</td>
<td>Electricity, gas, and water (Utilities)</td>
</tr>
<tr>
<td>SIC 5</td>
<td>Constr.</td>
<td>Construction</td>
</tr>
<tr>
<td>SIC 6</td>
<td>Retail</td>
<td>Wholesale and retail trade, hotels, and restaurants</td>
</tr>
<tr>
<td>SIC 7</td>
<td>Transp.</td>
<td>Transport, storage, and communication</td>
</tr>
<tr>
<td>SIC 8</td>
<td>Fin.</td>
<td>Finance, insurance, real estate, and business services</td>
</tr>
<tr>
<td>SIC 91</td>
<td>Govt.</td>
<td>General government</td>
</tr>
<tr>
<td>SIC 92-96, 99</td>
<td>Pers.</td>
<td>Community, social and personal services</td>
</tr>
<tr>
<td>SIC 91</td>
<td>Govt.</td>
<td>General government</td>
</tr>
</tbody>
</table>