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Watts happening to work? The labour market effects of South Africa´s electricity crisis

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April 2024

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The collaboration is between the United Nations University World Institute for Development Economics Research (UNU-WIDER), the National Treasury of South Africa, the South African Revenue Services, and other universities and institutes. It is funded by the National Treasury of South Africa, the Delegation of the European Union to South Africa and UNU-WIDER through the Institute's contributions from Finland, Sweden, and the United Kingdom to its research programme.

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Watts happening to work? The labour market effects of South Africa's electricity crisis

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Abstract: Frequent electricity outages threaten to impede the benefits of expanded access achieved by many developing countries in recent decades. A large literature documents these negative effects, however almost none consider labour market effects. This paper merges labour force survey microdata with high-frequency electricity supply and demand data to provide the first estimates of the relationships between outages and labour market outcomes in South Africa, a country characterized by frequent, severe outages referred to as load shedding. Exploiting temporal variation in outage incidence and intensity, we find that load shedding is associated with significantly lower employment rates, working hours, and earnings on average. Employment appears more sensitive relative to intensive margin outcomes, threatening job creation and preservation efforts. These negative relationships, however, are not evident for low levels of load shedding, but their strength markedly increases with load shedding intensity. We document further heterogeneity by firm size and industry, highlighting the vulnerability of jobs in manufacturing. Overall, our findings suggest that the South African labour market is largely insensitive to relatively low levels of load shedding; however, high levels appear especially costly.

Key words: electricity outages, labour market, developing country, South Africa, load shedding

JEL classification: J21, J23, J31, L94

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1 Introduction

Electricity characterizes modern-day life and is generally considered a key input into the production of most goods and services globally. In developing countries, electricity access has greatly improved in recent decades to reach 90 per cent of individuals in low- and middle-income countries as of 2021 (World Bank 2024). Despite this significant development, access alone is a necessary but insufficient criterion to achieve meaningful gains in development outcomes. Electricity supply in many lower-income countries, especially those in sub-Saharan Africa, is often characterized by inconsistency and inefficiency, with frequent and long-lasting outages serving as the consequence. By forcing households and firms to maintain a stock of alternatives, such as diesel generators and back-up batteries, both predictable and unpredictable outages raise the private and social costs of energy services, hindering the benefits of improved access (Andersen and Dalgaard 2013; Fakih et al. 2020; Lee et al. 2020; Meles 2020; Meles et al. 2021; Elliott et al. 2021; Hashemi 2021; Mensah 2024).

A large empirical literature documents the adverse effects of power outages in developing countries on various outcomes, such as economic growth, firm productivity, firm sales, and other production process outcomes (Arnold et al. 2008; Eberhard et al. 2011; Andersen and Dalgaard 2013; Fattouh and El-Katiri 2013; Amadi 2015; Fisher-Vanden et al. 2015; Cole et al. 2018; Magongo and Sacolo 2018; Fakih et al. 2020; Meles 2020; Elliott et al. 2021; Chen et al. 2022, 2023; Mensah 2024). These effects appear particularly strong for economic agents who are unable to mitigate outages, such as through the use of self-generation (Cole et al. 2018). These negative effects are reflected in relatively large estimates of demand for electricity reliability in such contexts (Carlsson et al. 2020; Hashemi 2021; Meles et al. 2021). Almost no studies, however, examine the implications of electricity outages for labour markets. Mensah (2024) serves as one exception: They estimate significant negative employment effects ranging between 4.7 and 13.5 percentage points among a sample of African countries, with larger effects on non-agricultural, energy-intensive, and private sectors as well as skilled jobs.

This study seeks to contribute to this relatively sparse literature on the labour market effects of electricity outages in developing countries, using South Africa as a case study—a country already characterized by one of the highest unemployment rates globally. While boasting almost universal access (Statistics South Africa 2023), since the end of 2007 the country has been subjected to rotational, scheduled electricity outages which seek to reduce electricity demand to meet a constrained supply, referred to as load shedding. The frequency and intensity of these outages have increased substantially in recent years, and while efforts are underway to improve the performance of the system, electricity supply is projected to remain significantly constrained in the medium term. While several studies document negative effects of these outages on economic growth (Andersen and Dalgaard 2013; Volkwyn and Kleynhans 2014; Walsh et al. 2021, 2023; Mabugu and Inglesi-Lotz 2022; South African Reserve Bank 2023), which are anticipated to translate into significant labour market effects, there is a striking absence of such evidence.[1]

We merge individual-level, nationally representative labour force survey data with macroeconomic data and high-frequency electricity production and consumption data not available in the public domain and privately provided by South Africa's national electricity supplier from 2008 to 2023 and exploit temporal variation in the incidence and intensity of outages to estimate their associations with labour market outcomes. Making use of multiple measures of load shedding, we analyse four outcomes in particular on both the extensive and intensive margins: employment, working hours, hourly wages, and monthly earnings. We estimate associations on average and additionally consider heterogeneity by outage intensity, firm size, and industry. Our results show that there is a significant, negative relationship between

[1] The Minister of Electricity has publicly stated that load shedding caused 650,000 job losses in 2022 (Nkanjeni 2023), however the source of this estimate is unclear.

these outages and employment, working hours, and monthly earnings. A null association with hourly wages suggests the monthly earning reductions are driven by working hour reductions. All these associations are, however, not evident for low levels of load shedding but tend to significantly increase with load shedding intensity. We also document notable heterogeneity with respect to firm size and industry. Workers in large firms exhibit vulnerability with respect to all outcomes, while only negative but larger working hour adjustments are evident for small firms. A strong, negative employment association for the manufacturing industry drives the average association, while most industries exhibit significant downward working hour adjustments. Industry-specific estimates for wages and earnings are, however, mixed.

Overall, our analysis provides further evidence of the negative effects of electricity outages on labour market outcomes in developing countries. In South Africa in particular, it suggests that the labour market is largely insensitive to relatively low levels of outages; however, high levels are particularly costly. Our study makes several contributions to existing literatures. First and broadly, this study is situated within the large literature of the economic effects of electricity outages in developing countries (Arnold et al. 2008; Eberhard et al. 2011; Andersen and Dalgaard 2013; Fattouh and El-Katiri 2013; Amadi 2015; Fisher-Vanden et al. 2015; Cole et al. 2018; Magongo and Sacolo 2018; Fakih et al. 2020; Meles 2020; Chen et al. 2023). It thus contributes to the literature on the relationship between infrastructure improvements and economic development (Dinkelman 2011; Hjort and Poulsen 2019; Lee et al. 2020; Fried and Lagakos 2021; Hjort and Tian 2021; Abbasi et al. 2022; Mensah and Traore 2024). Primarily, it contributes to the relatively scant literature on the labour market implications of electricity outages, referred to previously (Mensah 2024). Notably, however, by accessing high-frequency electricity data not available in the public domain, to our knowledge it is the first to examine the labour market effects of these outages in South Africa. While our estimates are not causal in nature, they are intended to serve as an important first step in filling this gap in the literature.

The rest of this paper is organized as follows. Section 2 provides an overview of these electricity outages in South Africa, while in Sections 3 and 4 we describe the data and our econometric strategy. The results are presented in Section 5 followed by a series of robustness tests in Section 6. Section 7 concludes.

2 An overview of electricity outages in contemporary South Africa

As previously stated, South Africa has been subjected to rotational, scheduled electricity outages implemented by the country's primary electricity supplier, Eskom, to reduce electricity demand to meet a constrained electricity supply since the end of 2007. Load shedding, as one component of manual load reduction (MLR) together with load curtailment, [2] is an internationally recognized engineering term and differs from blackouts in that it is controlled and affects a limited, spatially-defined area for a scheduled duration. In contrast, blackouts uncontrollably occur without warning and affect many if not all areas simultaneously for an unpredictable duration. It is widely documented that these outages in the country are primarily due to a large amount of unplanned maintenance due to plant breakdowns at Eskom's aging coal-fired power stations (City of Cape Town 2020; Walsh et al. 2021; South African Reserve Bank 2022, 2023). These stations dominate the country's electricity supply mix and, with 80 per cent of them having reached or being past their mid-life cycle, experience frequent breakdowns (Eskom 2023).

Load shedding is rotational in that suburbs are subjected to varied schedules in two- to four-hour blocks, but is implemented at the national level at a given level of severity or 'stage' depending on the extent of

[2] Load curtailment refers to an agreement between Eskom and several large industrial customers to reduce their electricity consumption.

the electricity shortage. The City of Cape Town municipality serves as the single exception. It is often able to reduce the intensity of these outages by up to 2,000 megawatts (MW) daily or four fewer hours per day, due to the operation of its own hydro pump station and gas turbines (City of Cape Town 2020).[3] We account for this source of variation in our modelling to follow. At the time of writing, eight stages had been developed with each stage requiring more energy to be shed nationally. Stage 1 allows for up to 1,000 MW to be shed; Stage 2 up to 2,000 MW; Stage 3 up to 3,000 MW; and so on. Stage 6 has been the highest stage officially recorded, however demand has been reduced by more than 6,000 MW during some periods.[4]

The frequency and severity of these outages has increased significantly in recent years, resulting in the President declaring a national state of disaster in February 2023.[5] At the end of 2022, load shedding was in place for approximately 50 per cent of hours in the average month, up from 10 per cent in 2015 (South African Reserve Bank 2022). This worsened further in 2023 which, at the time of writing, served as the worst year of load shedding on record. As we show later, over 9,600 gigawatt hours (GWh) of electricity demand was not met for the first five months of 2023 alone, compared to over 8,100 GWh for the whole year prior. While efforts are underway to improve the performance of existing power stations through major repairs, maintenance projects, and new generation capacity, electricity supply is projected to remain significantly constrained in the medium term (Eskom 2022).

Several studies have estimated or simulated the macroeconomic consequences of load shedding in South Africa, with a focus on output. While the data, methods, and magnitudes of estimates differ, there is a broad consensus of an inverse relationship between economic growth and load shedding (Andersen and Dalgaard 2013; Volkwyn and Kleynhans 2014; Walsh et al. 2021, 2023; Mabugu and Inglesi-Lotz 2022; South African Reserve Bank 2023). Walsh et al. (2021) estimate that load shedding cost the South African economy ZAR43.5 billion in 2022 South African Rands (US$6.2 billion in purchasing power parity (PPP)[6] terms) from 2007 to 2019, approximately equivalent to the impact of the 2008/09 global financial crisis. During recent years, updated estimates from Walsh et al. (2023) suggest this cost has increased fivefold to ZAR224 billion (about US$32 billion PPP) for 2020 to 2022 alone. The South African Reserve Bank (2023) forecasted that load shedding reduced real gross domestic product (GDP) growth by two percentage points in 2023. Expectedly, existing research suggests that these output effects are heterogenous across industries. Consistent with Mensah's (2024) analysis of other African countries, both Volkwyn and Kleynhans (2014) and Walsh et al. (2021, 2023) identify stronger associations for energy-intensive industries, namely manufacturing, transport and communication, retail trade, and agriculture. As stated previously, these effects are anticipated to translate into significant labour market effects. There is, however, a striking absence of such evidence.

[3] Specifically, the Steenbras Hydro Pump Station, a pumped storage scheme, has capacity to produce 180 megawatts of hydroelectricity. The station acts like a battery. Water from the upper storage reservoir is released to the lower reservoir to generate electricity, and when demand is low, turbines pump the water back up to be reused the next day. As such, the amount of electricity that it can generate in one day is limited by the capacity of the lower reservoir. The city also operates its own gas turbines which produce an additional 78 megawatts of electricity but operate for much shorter periods after maximizing the output of the hydro pump station due to more expensive fuel that is required. Because hydro pump stations require specific geographic conditions such as mountainous areas to operate, the city is the only municipality in the country to own and operate one of these stations, with other municipalities not having their own alternative sources of electricity.

[4] This need not imply that load shedding stages are misleading. For instance, stage 6 load shedding in excess of 6,000 MW shed can be attributed to high stages of load shedding combined with low stages of load curtailment, simultaneously.

[5] While the national state of disaster has since been revoked, the frequency and severity of load shedding remain significant.

[6] Conversion based on the World Bank's PPP conversion factors.

3 Data

First, we merge individual-level, nationally representative labour force survey data with macroeconomic data and national-level electricity production and consumption data for over 15 years from 2008 to 2023. These comprise three distinct datasets, and given that load shedding can vary daily, our choice of datasets is guided by data availability and frequency. First, the labour force data is sourced from Statistics South Africa's (StatsSA) Quarterly Labour Force Surveys (QLFS), appended from when it began in the first quarter of 2008 (2008Q1) until 2023Q2—the latest period of data at the time of writing. The QLFS is a nationally representative, individual-level household survey containing detailed data on labour market activities, and although conducted quarterly, serves as the country's most frequent labour market data available in the country. The sample here is restricted to those of working age (15–64 years).

We also merge in raw, unimputed QLFS pre-tax wage data from 2010Q1 onwards privately provided to us by StatsSA.[7] This is important because the public domain data includes poor-quality wage imputations for workers who did not report them which, unfortunately, cannot be distinguished from the reported data. These have been shown to produce implausible and volatile estimates (Wittenberg 2017; Bhorat et al. 2021; Kerr and Wittenberg 2021; Köhler et al. 2023; Köhler 2023; Köhler and Bhorat 2023). However, reliable results can be obtained when the underlying unimputed data is used after adjusting for outliers and missing data. We follow Köhler and Bhorat (2023) and adjust the raw data for both, using two parametric statistical techniques which are considered to be among the most effective methods for addressing implausible outlying values and item non-response (Wittenberg 2017; R. C. Daniels 2022). First, we adopt the studentized regression residual approach to address outliers in both tails of the distribution. This entails estimating an expanded Mincerian wage regression of the logarithm of monthly wages on a vector of observable covariates[8] using ordinary least squares (OLS), predicting and standardizing the residuals, and flagging observations with large residuals as outliers. Outliers are defined as those with absolute studentized residuals in excess of three, equivalent to about 1 per cent of observations who reported their wages, and are recoded as missing. Second, we use multiple imputation (MI) to impute wages for employed non-responders. MI is similar to stochastic imputation, but is advantageous in that it repeats the imputation process multiple times to produce multiple values of what the true data might be. We impute wages for workers who (i) neither reported their exact wage nor a wage bracket, (ii) only reported a bracket, or (iii) were identified as outliers. Because the missing wage data in the survey has a monotone pattern,[9] for each wave we first multiply impute a bracket for those in group (i) or (iii) by first estimating an ordered logit model on a vector of observable covariates,[10] and thereafter multiply impute log monthly wages based on the imputed bracket and the same vector using predictive mean matching with ten nearest neighbours. For observations in group (ii), the imputation process skips the first step. This process is repeated iteratively to arrive at ten imputations. The data are then combined using Rubin's (1987) rules for estimation and inference. Prior to these processes, in the

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[7] The QLFS only started collecting wage data in 2009Q3. However, the data for 2009Q3 and 2009Q4 have not been made available.

[8] The vector of observable covariates includes the usual Mincerian covariates—years of education and experience (and its squared term)—as well as age, sex, racial population group, province, an urban indicator, marital status, main industry and occupation, a public sector indicator, a formal sector indicator, a trade union membership indicator, and survey wave fixed effects

[9] The monotone missingness pattern is due to the questionnaire's skip logic. If bracket wage data is missing, then exact wage data will be missing.

[10] The selection of covariates is based on those which are required in the complete data model of interest, those which appear to determine missingness, and those which explain a considerable amount of the variance of log monthly wages. These are included in both imputation models, and include age, sex, racial population group, years of education, experience (and its squared term), province, an urban indicator, marital status, main industry and occupation, a public sector indicator, a formal sector indicator, frequency of wage payments, and a trade union membership indicator.

raw data about half of all workers in a given wave's sample reported an exact wage, 20 per cent did not but did report a bracket, and the remainder did not report any wage information at all (Köhler and Bhorat 2023). Following the outlier and MI processes, we obtain wage data for nearly all (94 per cent) workers in our sample.[11] While the interested reader is referred to Köhler and Bhorat (2023) for a comprehensive outline of these techniques, it should be noted that the resultant wage estimates are strongly robust to varying imputation algorithms and number of imputations.

Second, electricity data is sourced from privately provided, national-level, high-frequency data from Eskom since 2007 which contains both supply- and demand-side variables including electricity consumption and production, supply composition, and emissions. Our covariate of interest is manual load reduction (MLR), defined as the amount of electricity demand in megawatts (MW) that has been reduced due to both load shedding and load curtailment. MLR is of course not observed but instead estimated based on the difference between the national day-ahead demand forecast and actual demand while load shedding is in place. Unfortunately, the data does not allow us to decompose MLR into its components. Throughout our analysis, references to load shedding refer to MLR unless explicitly stated otherwise. Because this dataset is at a much higher frequency (sometimes by the hour), we aggregate it to the quarterly frequency by calculating the maximum daily MLR peak for each quarter and thereafter merge it with the QLFS. As such, our analysis relies on temporal variation in load shedding prevalence and intensity at the quarterly frequency.[12]

Third and finally, macroeconomic data is sourced from South Africa's central bank (the South African Reserve Bank or SARB). It includes real GDP at market prices in constant 2015 Rands, the interest or repo rate, and the real effective exchange rate. Explained in the following section, these variables serve as controls in our modelling approach and simply seek to minimize any bias in the bi-variate, temporal association between load shedding and a given labour market outcome. The selection of these are guided by their empirical roles as relevant macroeconomic determinants of these outcomes over a long time horizon (Boltho and Glyn 1995; Anyanwu 2013; Pattanaik and Nayak 2014; Oniore et al. 2015). Our results are, however, insensitive to the inclusion of further controls, such as government expenditure, gross fixed capital formation, imports, and exports. This data is also aggregated to the quarterly frequency through averaging and thereafter merged with the QLFS. All data are available until 2023Q2 inclusive.

Following the appending and merging of the above datasets, our final sample comprises nearly three million observations (n = 2,856,748) across 62 quarters or 15 and a half years. Unless specified otherwise, all estimates are weighted using sampling weights and account for the complex survey design through the use of strata and cluster variables available in the QLFS microdata.

4 Methodology

The primary aim of our analysis is to estimate the associations between load shedding, as measured using MLR, and labour market outcomes on both the extensive and intensive margins, on average, and by firm size and industry. To do so, we use the pooled sample of observations in the data described above to first descriptively examine the bi-variate associations between these outcomes and load shedding, and thereafter, we model these associations in a multivariate regression framework. We focus on four outcomes in particular: employment, working hours, real hourly wages, and real monthly earnings.

[11] Wages could not be imputed for 6 per cent of workers in the sample due to missing data on variables used in the imputation model, such as sectoral formality and marital status.

[12] Of course, load shedding varies considerably both across as well as within quarters, but unfortunately the quarterly frequency is the highest frequency of labour market data available to conduct the analysis here.

Hourly wages are derived using data on usual weekly hours worked and labour income adjusted to the weekly frequency. Monthly earnings are derived similarly but at the monthly frequency. We consider both hourly wages and monthly earnings because any effect on working hours will not necessarily translate into effects on hourly wages but will on monthly earnings. Both wages and earnings are adjusted for inflation and expressed in January 2023 South African Rands.

Our modelling approach primarily seeks to control for time-varying confounding variables to minimize any bias evident in the bi-variate associations. Given that our analysis relies on temporal variation in load shedding prevalence and intensity across quarters, our measure of load shedding is endogenous, and time-varying confounders which are unaccounted for will introduce sources of bias. For instance, a positive bi-variate association need not imply that load shedding positively affects a given outcome but instead may simply be the consequence of both growing over time. Alternatively, if load shedding is inversely correlated with real GDP, as the existing literature suggests, then a negative bi-variate association between load shedding and a given labour market outcome may simply reflect the relationship between output and the labour market. Using OLS, we first estimate the following simple specification to examine average conditional associations:

$$y_{it} = \beta_0 + \beta_1 loadshedding_t + \gamma M_t + \tau_t + \varepsilon_{it} \tag{1}$$

where y_{it} is one of the four outcomes of interest for individual i in period t: a binary employment dummy; weekly working hours; real hourly wages; or real monthly earnings. Data for the latter three outcomes are all transformed to the natural log scale. $loadshedding_t$ is the time-varying measure of load shedding which we define in three alternative ways to facilitate a more comprehensive and nuanced understanding of the relevant relationships. First, a binary indicator is used to reflect the association with a given outcome on average, regardless of the severity of load shedding. Second, a continuous variable is used to account for variation in severity on a continuum, measured as the estimated reduction in electricity demand in MW but transformed to the natural log scale.[13,14] This transformation allows us to interpret β_1 as a semi- or full-elasticity, depending on the outcome. Third, we use a categorical variable to account for variation in severity according to six load shedding stages. This measure may be particularly insightful given that, in practice, public announcements of load shedding more often reference a given stage as opposed to the number of MW estimated to be shed. Here, no load shedding serves as the reference category, stage 1 refers to up to and including 1,000 MW shed, stage 2 up to and including 2,000 MW shed, and so on, up to stage 6 which refers to up to 6,000 MW shed or more.

Finally, M_t is a vector of time-varying macroeconomic controls referenced in Section 3, τ_t is quarter fixed effects (FE) used to control for seasonality given that load shedding tends to be more severe in winter, and ε_{it} is the error term. Because our approach relies on temporal variation across quarters, we avoid additionally controlling for time trends which would diminish variability in $loadshedding_t$, as well as individual-level covariates which vary across individuals cross-sectionally. Our results are, however, very insensitive to their inclusion.[15] We additionally control for a binary indicator for observations in the City of Cape Town district municipality to account for the local government often being able to reduce the intensity of these outages, as described in Section 2. Despite the inclusion of these controls,

[13] Given that the level of this variable will be zero for periods of no load shedding, deriving the log value will result in these observations being omitted from the model. To avoid this outcome and retain data when load shedding was not in place, we adopt the common approach of adding a small constant (one) to all values before taking the log transformation.

[14] While the continuous load shedding variable contains count data, non-linear estimators are not necessary given that in this analysis the variable serves as a predictor, as opposed to an outcome, for which there are no distributional requirements in generalized linear models.

[15] For instance, when we control for sex, race, educational attainment, marital status, and province of residence, both the coefficient magnitudes and levels of precision are unaffected.

we are agnostic that they absorb all sources of bias in our endogenous load shedding variable simply because the incidence and intensity of load shedding are non-randomly distributed over time.[16] As such, it should again be emphasized that these models do not allow us to infer any causal effects, but instead simply provide estimates of conditional correlations; that is, the correlations between load shedding and labour market outcomes after accounting for variation in the above factors.

To analyse how these average associations vary across firms of varied sizes and industries, we adjust specification (1) to include an interaction term of $loadshedding_t$ with a measure of either firm size or industry and estimate the following specifications using the employed sub-sample:

$$y_{it} = \beta_0 + \beta_1 loadshedding_t + \beta_2 size_{it} + \beta_3 loadshedding_t \times size_{it} + \gamma M_t + \tau_t + {}_{it} \tag{2}$$

$$y_{it} = \beta_0 + \beta_1 loadshedding_t + \beta_2 industry_{it} + \beta_\theta loadshedding_t \times industry_{it} + \gamma M_t + \tau_t + {}_{it} \tag{3}$$

where $size_{it}$ is a binary dummy variable equal to one if individual i worked in a small firm, defined as employing less than 50 workers in period t and zero for larger firms. We adopt this categorization due to the limited number of firm size options available in the survey.[17] $industry_{it}$ is a categorical variable referring to individual i's main industry in period t according to one-digit Standard Industrial Classification (SIC) codes. Here, y_{it} again represents one of the four outcomes of interest, with the exception of employment which is now measured as weighted employment counts on a natural log scale after the data is aggregated to the quarterly firm-size level for specification (2) or quarterly industry level for specification (3).[18] We then estimate average marginal effect estimates (or conditional correlations) of load shedding on a given outcome for each value of $size_{it}$ and $industry_{it}$ by deriving the derivative of y_{it} with respect to $loadshedding_t$; in other words, by taking the linear combination of β_1 and β_3 in specification (2) and β_1 and β_θ in specification (3) where $\theta \in [1;10]$.[19]

5 Results

5.1 Descriptive statistics

In this section, we descriptively examine the relationship between load shedding and the four outcomes of interest. First, making use of the data provided by Eskom, it is clear that the incidence and severity of load shedding has increased significantly in recent years, and that this outcome is attributable to a contraction in electricity generation capacity or supply. Figure 1 presents high frequency (daily) time series plots of the difference between electricity supply and demand in panel (a) and load shedding

[16] Estimating a causal effect would entail exploiting some source of plausibly random or quasi-random variation in load shedding incidence or intensity. However, for both practical and ethical reasons, load shedding is not administered randomly across time or space in South Africa. However, through the use of a difference-in-differences design, future research may take advantage of the facts that load shedding did not occur during certain years, that certain key points are sometimes excluded as defined in the relevant National Regulatory Standard, and as described previously, the City of Cape Town often experiences reduced load shedding intensity relative to other municipalities.

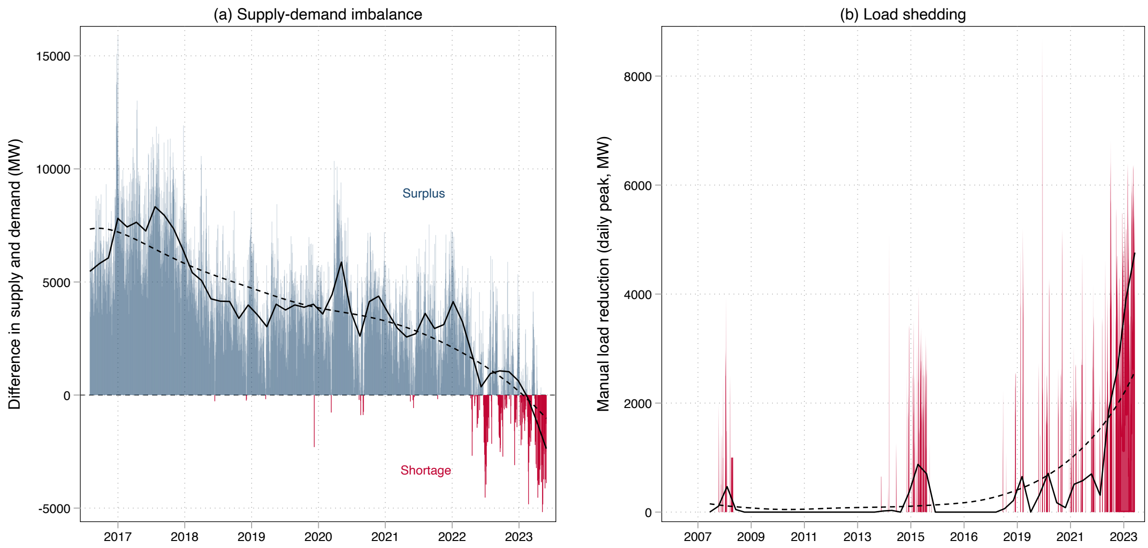
[17] Firm size expressed continuously is not available in the survey. Instead, seven categories are available, with the largest being 50 workers or more.

[18] Estimating either specification using a binary employment indicator as the outcome is not possible at the individual level given that both firm size and industry are conditional on being employed.

[19] β_1 alone then represents the conditional correlation between load shedding and a given outcome for the reference group in a given specification.

incidence and severity in panel (b).[20] The plots of supply and demand are presented separately in Figure A1 in the appendix. Recall that the magnitude of load shedding is not necessarily equal to that of shortage given that it is not observed but instead estimated based on the difference between the national day-ahead demand forecast (a counterfactual) and actual demand while load shedding is in place.[21] Each plot is overlaid with local polynomial and local linear smoothing plots to account for daily and seasonal fluctuations.

Figure 1: Electricity supply-demand imbalance and load shedding in South Africa, 2007–23



Note: electricity demand is measured as the daily peak in the hourly average demand that needs to be supplied by all resources that Eskom has contracts with, and supply is measured as the total available capacity available from all generation resources that Eskom has contracts with at the daily demand peak, including non-commercial units and renewables. Manual load reduction includes both load shedding and load curtailment. Solid and dashed lines represent local polynomial and local linear smoothing plots, respectively.

Source: authors' calculations based on electricity production and consumption data provided by Eskom.

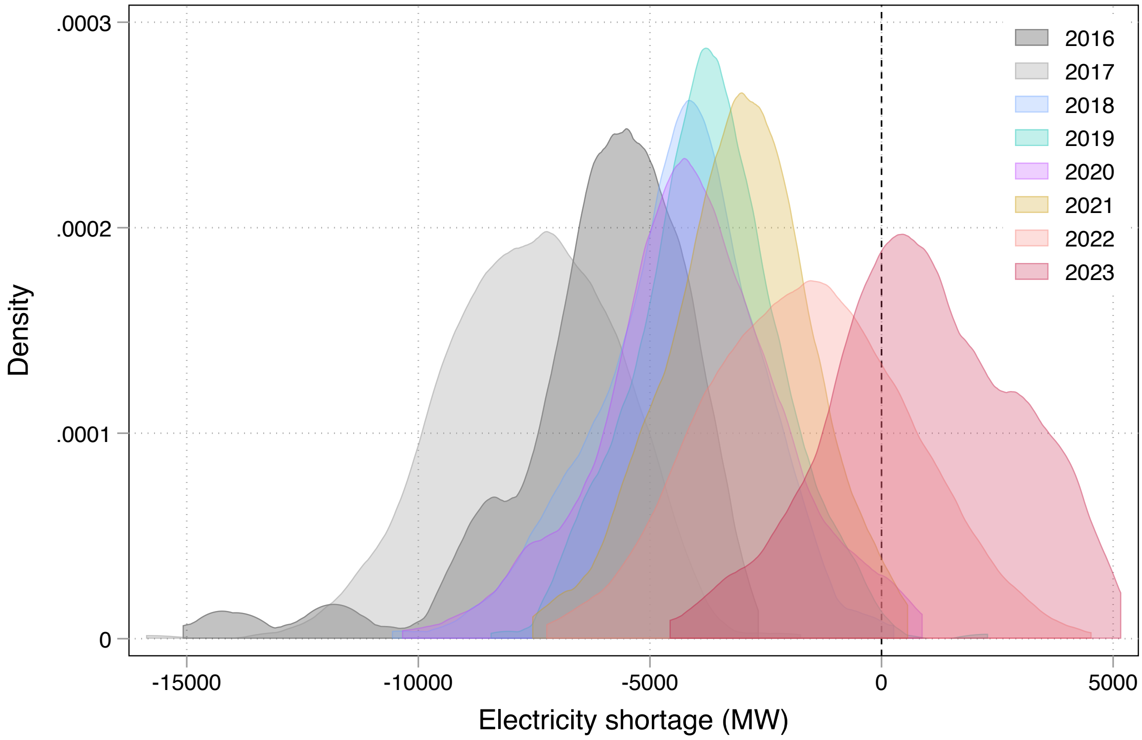
As shown in panel (a), a surplus of electricity is evident for most of the period, however there is a clear downward medium-term trend in the difference between electricity supply and demand resulting in significant shortages in recent years. While prior to 2022 shortages occurred periodically, a much higher frequency, intensity, and persistence of shortages is evident for most of 2022 and 2023. As shown in Figure A1 in the appendix, this downward trend is driven by a contraction in supply, while demand was relatively constant over the period. Supply decreased by over 25 per cent from a daily average of nearly 39,000 MW in 2017 to 29,000 MW in 2023, while demand decreased only marginally (3 per cent) from 31 ,000 MW to 30,000 MW over the same period. The year 2023 serves as the first year where average demand exceeded supply as measured here. Load shedding serves as the consequence of this shortage which, as described in Section 2 and shown in panel (b), was first implemented in late 2007. In 2008, just 171 MW were shed per day on average, while no load shedding occurred between 2009 and 2012 inclusive. Load shedding was re-introduced in 2013 and increased to 574 MW in 2015. While it remained in place during the pandemic, it was marginally less severe at 320–426 MW between 2020 and 2021. Recent years have experienced the worst load shedding to date. Over 1,660 MW were shed in the average day in 2022, more than doubling to 4,011 MW in 2023, representing over 23 times more energy shed relative to when load shedding began. The higher frequency and intensity of load shedding is also

[20] Data on electricity supply and demand as measured in panel (a) is only available from 2016Q3 onwards, while data on manual load reduction is available from 2007 onwards.

[21] Moreover, to ensure the stability of the electricity grid, the magnitude of MLR is in many instances larger than the magnitude of the difference in electricity demand and supply.

evident when examining changes in the distribution of daily electricity shortages over time, as presented in Figure 2. As similarly reflected in Figure 1, while a surplus is evident for most of the period, there is a clear rightwards shift in the distribution towards more frequent and severe shortages over time.

Figure 2: Distribution of daily electricity shortages in South Africa, 2016–23



Note: electricity shortage is measured as electricity demand less supply. Demand is measured as the daily peak in the hourly average demand that needs to be supplied by all resources that Eskom has contracts with. Supply is measured as the total available capacity available from all generation resources that Eskom has contracts with at the daily demand peak, including non-commercial units and renewables.

Source: authors' calculations based on electricity production and consumption data provided by Eskom.

Figure 3 presents trends in three of the four labour market outcomes of interest over the full period, accompanied by reference lines for three distinct load shedding periods as observed above. The figure here includes hourly wages, while the equivalent figure which includes monthly earnings is included in Figure A2 in the appendix. The figure yields several significant observations of the South African labour market over the last 15 years. Considering pre-pandemic trends, the share of the working-age population employed dropped considerably in 2009 following the global financial crisis from 46 to 42 per cent and gradually but only partially recovered in the decade thereafter. Mean working hours has consistently declined at a relatively constant rate, from over 45 hours per week in 2008 to 43 hours in 2019. Concurrently, mean wages rose in real terms from about ZAR70 (US$10 PPP) per hour in 2010 to ZAR76 (US$11 PPP) per hour in 2019—9 per cent over the whole pre-pandemic period or 1.4 per cent in the average year. Mean real monthly earnings also increased but by a smaller degree, reflecting the concurrent reduction in working hours, from ZAR12,500 (US$1,800 PPP) in 2010 to ZAR13,100 (US$1,885 PPP) in 2019, or 0.5 per cent per year on average (see Figure A2).

Figure 3: Trends in employment, working hours, and real hourly wages in South Africa, 2008Q1–2023Q2

Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. Wage data privately provided by StatsSA, is only available from 2010Q1 onwards, and is adjusted for outliers and missing values. Shaded areas represent 95 per cent confidence intervals. Vertical reference lines represent distinct periods when load shedding (LS) was in place.

Source: authors' calculation based on QLFS 2008Q1–2023Q2.

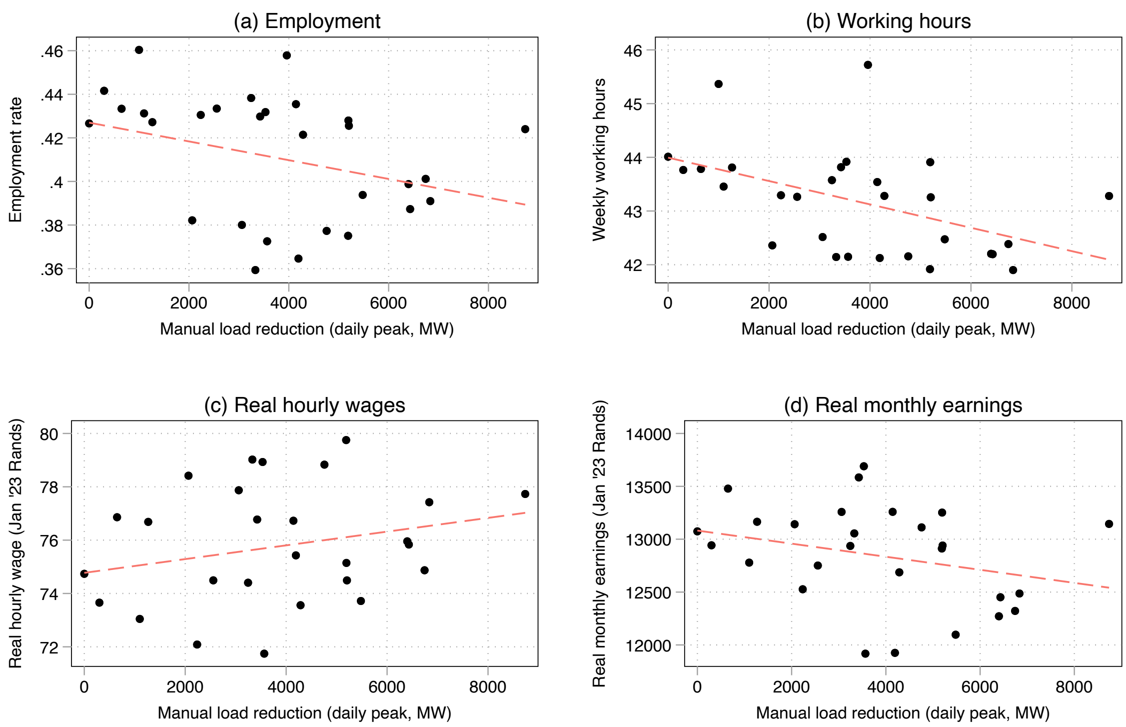
The onset of the COVID-19 pandemic in 2020Q2 significantly disrupted the South African labour market. Employment contracted by over 14 per cent (or over 2.2 million jobs on net), while concurrently, usual working hours reduced by 3 per cent (with a larger contraction in reported actual working hours) which partially reflects a surge in the share of workers furloughed from 1 to 16 per cent, and conversely, real hourly wages rose by 20 per cent.[22] This latter increase is largely mechanical. Over 70 per cent of this latter dynamic is explained by a composition effect, with lower-wage workers being up to three times more likely than their higher-earning counterparts to experience job loss and hence drop out of the wage distribution entirely (see Köhler and Bhorat (2023) for a detailed analysis of wage dynamics during the pandemic). Consistent with the global literature, the regressivity of job loss has been largely attributed to lower-wage workers' lower likelihood of both being able to work from home and work in occupations deemed 'essential'. As of 2023Q2, the labour market had only partially recovered. While real hourly wages had returned to their pre-pandemic level, employment (in relative terms), working hours, and real monthly earnings remained below. A large empirical literature documents these dynamics, overall and for specific sub-groups of interest (for instance, see Bassier et al. 2023; Bhorat, Köhler, et al. 2020; Bhorat, Thornton, et al. 2020; Casale and Posel 2021; Casale and Shepherd 2022; R. Daniels and Casale 2022; Espi-Sanchis et al. 2022; Hill and Köhler 2021; Köhler et al. 2022, 2023; Köhler and Bhorat 2023; Mosomi and Thornton 2022; Ranchhod and Daniels 2021; Rogan and Skinner 2020, 2022; Shifa et al. 2021, 2022; Turok and Visagie 2022; Yu et al. 2023). Importantly, these dynamics may confound our estimated relationships of interest given the greater incidence and severity of load shedding during the pandemic, particularly after 2021. We adopt several approaches to attempt to address this in

[22] As shown in Figure A2 in the appendix, real monthly earnings also rose at the pandemic's onset but by a smaller rate (8.5 per cent).

the robustness test section to follow, however we urge the reader to keep this in mind throughout the analysis.

We next examine the bi-variate association between load shedding and our four outcomes of interest. Given that our approach relies on temporal variation in load shedding, it should be emphasized that these associations at least partially simply reflect changes in a given outcome alongside intensifying load shedding over time. Figure 4 presents individual binned scatterplots of load shedding on a continuous scale against each outcome accompanied by a linear regression line.[23] For most outcomes we observe a negative and statistically significant association, with a stronger association on the extensive margin (employment) and weaker association on the intensive margin (working hours and earnings). Marginally and on average, 1,000 MW of load shedding (equivalent of one additional stage) is associated with a 0.5 percentage point lower employment rate. In relative terms, this association is of a non-negligible magnitude.[24]

Figure 4: Binned scatterplots of load shedding against labour market outcomes in South Africa



Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. Wage and earnings data privately provided by StatsSA, is only available from 2010Q1 onwards, and is adjusted for outliers and missing values. Each plot uses 50 equal-sized bins of the variable on the horizontal axis.
Source: authors' calculations based on QLFS 2008Q1–2023Q2 as well as electricity production and consumption data provided by Eskom.

Considering the other outcomes, 1,000 MW of load shedding is associated with 0.25 fewer working hours (or 15 minutes) per week or approximately one hour per month, and ZAR62.50 (US$9 PPP) lower real monthly earnings. Compared to employment, these intensive margin associations are all relatively muted. On the other hand, as shown in panel (c), 1,000 MW of load shedding is associated with higher

[23] Owing to our very large sample sizes, we use binned plots as opposed to traditional ones which plot every observation simply for ease of interpretability.

[24] When considering employment levels, as shown in Figure A3 in the appendix, conversely, we estimate a positive association, which is not unexpected given that both employment levels and the severity of load shedding have grown over time.

real hourly wages. While this association is quite weak, it may reflect a composition effect—that is, if load shedding results in heterogenous disemployment effects across the wage distribution, wages will artificially be higher if such effects are concentrated among lower-wage workers. As discussed prior, these unconditional associations may be biased by any time-varying confounders, which we attempt to account for in our modelling in the next section. Importantly, however, these associations are not driven by dynamics during the COVID-19 pandemic. As shown in Figure A4 in the appendix, the associations are virtually unchanged when data collected during the pandemic period are omitted.[25]

5.2 Modelling results

Average results

In this section examine the results of our multivariate modelling exercise as per specification (1) on the conditional associations between load shedding and the four outcomes of interest. The relevant estimates for employment, working hours, hourly wages, and monthly earnings are presented in Tables 1, 2, 3, and 4, respectively. Overall, the results suggest that in response to load shedding, the labour market adjusts negatively on both the extensive and intensive margins on average, with larger effects on the former. That is, load shedding is negatively associated with the probability of employment and, conditional on employment, is negatively associated with working hours and real monthly earnings, but not real hourly wages. These intensive margin adjustments then imply that reductions in monthly earnings are driven by reductions in working hours and not hourly wages. These results hold when subject to either the binary or continuous load shedding measure and also highlight significant heterogeneity with respect to load shedding intensity, with typically larger associations for higher amounts of load shedding but no association for low amounts.

As shown in column (1) in Table 1, periods of load shedding are associated with a 1.7 percentage point lower employment probability, on average and relative to periods with no load shedding. Given the inclusion of quarter fixed effects, this result is not driven by seasonal variation throughout the year. After controlling for the vector of time-varying macroeconomic covariates, the coefficient reduces marginally to 1.1 percentage points but remains highly significant. This is equivalent to 2.6 per cent using the mean employment rate of 42 per cent in the pooled sample. As a thought experiment, under the explicit assumption of causality and using the mean employment level for the last full year in our data, this estimate translates into nearly 420,000 net jobs lost. The coefficients on the continuous measure in columns (3) and (4) are qualitatively similar but speak to load shedding intensity as opposed to prevalence and, given the log scale, are semi-elasticities and hence are subject to a different interpretation. They suggest that a 10 per cent increase in load shedding intensity is associated with a 0.02 percentage point lower employment probability on average. This association is insensitive to the inclusion of macroeconomic controls.

[25] Specifically, given the pandemic's onset in South Africa at the end of March 2020 and the five subsequent infection waves experienced through to June 2022, as well as the repeal of all remaining pandemic-related restrictions in June 2022, data from 2020Q2 to 2022Q2 inclusive are selected for omission.

Table 1: Model estimates of the association between load shedding and employment

	(1)	(2)	(3)	(4)	(5)	(6)
Load shedding measure						
(i) Binary	-0.017***	-0.011***				
	(0.002)	(0.002)				
(ii) Continuous			-0.002***	-0.002***		
			(0.000)	(0.000)		
(iii) Stage (base = 0)						
Stage 1					0.019***	0.011***
					(0.002)	(0.002)
Stage 2					0.006**	0.009***
					(0.003)	(0.003)
Stage 3					-0.011***	-0.008***
					(0.003)	(0.003)
Stage 4					-0.022***	-0.014***
					(0.002)	(0.002)
Stage 5					-0.028***	-0.016***
					(0.003)	(0.003)
Stage 6					-0.025***	-0.024***
					(0.003)	(0.002)
Quarter FE	✓	✓	✓	✓	✓	✓
Macroeconomic controls	✗	✓	✗	✓	✗	✓
Constant	0.430***	0.390***	0.431***	0.379***	0.434***	0.368***
	(0.002)	(0.022)	(0.002)	(0.022)	(0.002)	(0.022)
Observations	2 856 719	2 856 719	2 856 719	2 856 719	2 856 719	2 856 719
R^2	0.000	0.004	0.000	0.004	0.001	0.004

Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. FE = fixed effects. Macroeconomic controls = real GDP, the interest or repo rate, and the real effective exchange rate. All models with macroeconomic controls additionally control for a City of Cape Town district municipality dummy. Standard errors presented in parentheses. *** p<0.01; ** p<0.05; * p<0.10.
Source: authors' calculations based on QLFS 2008Q1–2023Q2 as well as electricity production and consumption data provided by Eskom.

Examining how this association may vary non-linearly across load shedding stages, the estimates in column (6) imply that employment is insensitive to low degrees of load shedding (stages 1 and 2, equivalent to up to 2,000 MW of unmet demand). However, we observe a statistically significant, negative, and non-linear gradient from stage 3 upwards. While stage 3 load shedding is associated with a 0.8 percentage point lower employment rate, this increases to 1.4 percentage points for stage 4—a statistically significant difference. The estimate for stage 5 is not statistically different from that of stage 4, but notably, stage 6 load shedding is associated with a 2.4 percentage point lower employment rate. This is more than double the average association as per column (2) and three times larger than the stage 3 estimate. This suggests that, on the extensive margin, the South African labour market is largely insensitive to relatively low levels of load shedding; however, high levels are particularly costly.

Now turning to extensive margin adjustments, the estimates relating to working hours are presented in Table 2. We estimate a significant and negative average association between load shedding and weekly working hours, regardless of load shedding measure. Similar to employment, we find that this association varies by load shedding intensity, and that it is non-existent for lower levels but stronger for higher levels. Column (2) shows that load shedding periods are associated with 1.3 per cent fewer working hours per week, or 5.6 per cent per month, again on average and relative to periods with no load shedding. From the pooled sample mean of 43.6 hours per week, this equates to just over half an hour per week or nearly 2.5 hours per month. Alternatively, as per column (4), on a continuous scale a 10 per cent increase in load shedding intensity is associated with 0.02 per cent fewer weekly working hours. Again, as shown in column (6), this association varies by the intensity of load shedding. Like employment, working hours appear insensitive to low degrees of load shedding (stages 1 and 2), but are negatively adjusted with every stage from and inclusive of stage 3 upwards. Stages 3 to 5 are associated with similar reductions in working hours, ranging between 1.1 and 1.4 per cent. On the other hand, stage 6 load shedding is associated with nearly 3 per cent fewer weekly working hours—again more than double the average association and nearly triple that of stage 3. While the magnitudes of these associations are smaller than that of employment, they again are suggestive of the (in)sensitivity of the labour market to relatively (low) high levels of load shedding.

Table 2: Model estimates of the association between load shedding and working hours

	(1)	(2)	(3)	(4)	(5)	(6)
Load shedding measure						
(i) Binary	-0.027***	-0.013***				
	(0.002)	(0.002)				
(ii) Continuous			-0.004***	-0.002***		
			(0.000)	(0.000)		
(iii) Stage (base = 0)						
Stage 1					0.004*	0.002
					(0.002)	(0.002)
Stage 2					-0.007**	0.004
					(0.003)	(0.003)
Stage 3					-0.028***	-0.012***
					(0.003)	(0.003)
Stage 4					-0.021***	-0.011***
					(0.002)	(0.002)
Stage 5					-0.033***	-0.014***
					(0.003)	(0.003)
Stage 6					-0.043***	-0.029***
					(0.002)	(0.002)
Quarter FE	✓	✓	✓	✓	✓	✓
Macroeconomic controls	✗	✓	✗	✓	✗	✓
Constant	3.734***	3.881***	3.735***	3.871***	3.736***	3.852***
	(0.001)	(0.018)	(0.001)	(0.018)	(0.001)	(0.019)
Observations	1 136 749	1 136 749	1 136 749	1 136 749	1 136 749	1 136 749
R^2	0.001	0.002	0.001	0.003	0.002	0.003

Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. FE = fixed effects. Macroeconomic controls = real GDP, the interest or repo rate, and the real effective exchange rate. All models with macroeconomic controls additionally control for a City of Cape Town district municipality dummy. Standard errors presented in parentheses. *** p<0.01; ** p<0.05; * p<0.10.
Source: authors' calculations based on QLFS 2008Q1–2023Q2 as well as electricity production and consumption data provided by Eskom.

Considering the estimates for real hourly wages and monthly earnings, we largely do not find any robust evidence that load shedding is associated with real hourly wages, but we do estimate consistently negative associations for real monthly earnings. As shown in Table 3, after controlling for quarter fixed effects and the vector of time-varying macroeconomic controls, hourly wages do not statistically differ between periods of load shedding and no load shedding on average. The estimates in column (6) also reveal that this association largely does not vary by the intensity of load shedding. Stage 5 serves as the exception, which is associated with nearly 4 per cent lower hourly wages. On the other hand, the estimates in Table 4 show that load shedding is negatively associated with real monthly earnings. On average, load shedding periods are associated with 1.7 per cent lower monthly earnings relative to periods with no load shedding, and a 10 per cent increase in load shedding intensity is associated with 0.02 per cent lower monthly earnings. As shown in column (6), we again find that higher (stages 3 to 5) but not low (stages 1 and 2) levels of load shedding exhibit this negative association. The stage 6 coefficient is also negative, but is lower in magnitude and is statistically insignificant. Taken together with the similar magnitudes of the working hours estimates alongside the null hourly wage estimates, this implies that the reduction in monthly earnings is driven by a reduction in working hours.

Table 3: Model estimates of the association between load shedding and real hourly wages

	(1)	(2)	(3)	(4)	(5)	(6)
Load shedding measure						
(i) Binary	0.023***	-0.008				
	(0.009)	(0.008)				
(ii) Continuous			0.003***	-0.001		
			(0.001)	(0.001)		
(iii) Stage (base = 0)						
Stage 1					-0.003	-0.023
					(0.014)	(0.014)
Stage 2					-0.019	-0.022
					(0.013)	(0.013)
Stage 3					0.019	-0.016
					(0.013)	(0.011)
Stage 4					0.035***	-0.016
					(0.011)	(0.012)
Stage 5					0.018	-0.038***
					(0.012)	(0.012)
Stage 6					0.034***	0.011
					(0.011)	(0.010)
Quarter FE	✓	✓	✓	✓	✓	✓
Macroeconomic controls	✗	✓	✗	✓	✗	✓
Constant	3.638***	3.704***	3.637***	3.721***	3.634***	3.714***
	(0.008)	(0.114)	(0.008)	(0.114)	(0.008)	(0.114)
Observations	889 148	889 148	889 148	889 148	889 148	889 148
R^2	0.000	0.006	0.000	0.006	0.000	0.006

Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. FE = fixed effects. Macroeconomic controls = real GDP, the interest or repo rate, and the real effective exchange rate. All models with macroeconomic controls additionally control for a City of Cape Town district municipality dummy. Wage data privately provided by StatsSA, is only available from 2010Q1 onwards, and is adjusted for outliers and missing values. Standard errors presented in parentheses. *** p<0.01; ** p<0.05; * p<0.10.
Source: authors' calculations based on QLFS 2010Q1-–2023Q2 as well as electricity production and consumption data provided by Eskom.

Table 4: Model estimates of the association between load shedding and real monthly earnings

	(1)	(2)	(3)	(4)	(5)	(6)
Load shedding measure						
(i) Binary	-0.003	-0.017**				
	(0.009)	(0.008)				
(ii) Continuous			-0.000	-0.002**		
			(0.001)	(0.001)		
(iii) Stage (base = 0)						
Stage 1					-0.007	-0.017
					(0.014)	(0.014)
Stage 2					-0.023*	-0.016
					(0.013)	(0.013)
Stage 3					-0.004	-0.021**
					(0.013)	(0.011)
Stage 4					0.011	-0.019
					(0.011)	(0.012)
Stage 5					-0.010	-0.041***
					(0.012)	(0.012)
Stage 6					-0.004	-0.012
					(0.011)	(0.010)
Quarter FE	✓	✓	✓	✓	✓	✓
Macroeconomic controls	✗	✓	✗	✓	✗	✓
Constant	8.832***	9.102***	8.831***	9.102***	8.829***	9.089***
	(0.008)	(0.114)	(0.008)	(0.114)	(0.008)	(0.114)
Observations	889 156	889 156	889 156	889 156	889 156	889 156
R^2	0.000	0.006	0.000	0.006	0.000	0.006

Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. FE = fixed effects. Macroeconomic controls = real GDP, the interest or repo rate, and the real effective exchange rate. All models with macroeconomic controls additionally control for a City of Cape Town district municipality dummy. Wage data privately provided by StatsSA, is only available from 2010Q1 onwards, and is adjusted for outliers and missing values. Standard errors presented in parentheses. *** p<0.01; ** p<0.05; * p<0.10.
Source: authors' calculations based on QLFS 2010Q1-–2023Q2 as well as electricity production and consumption data provided by Eskom.

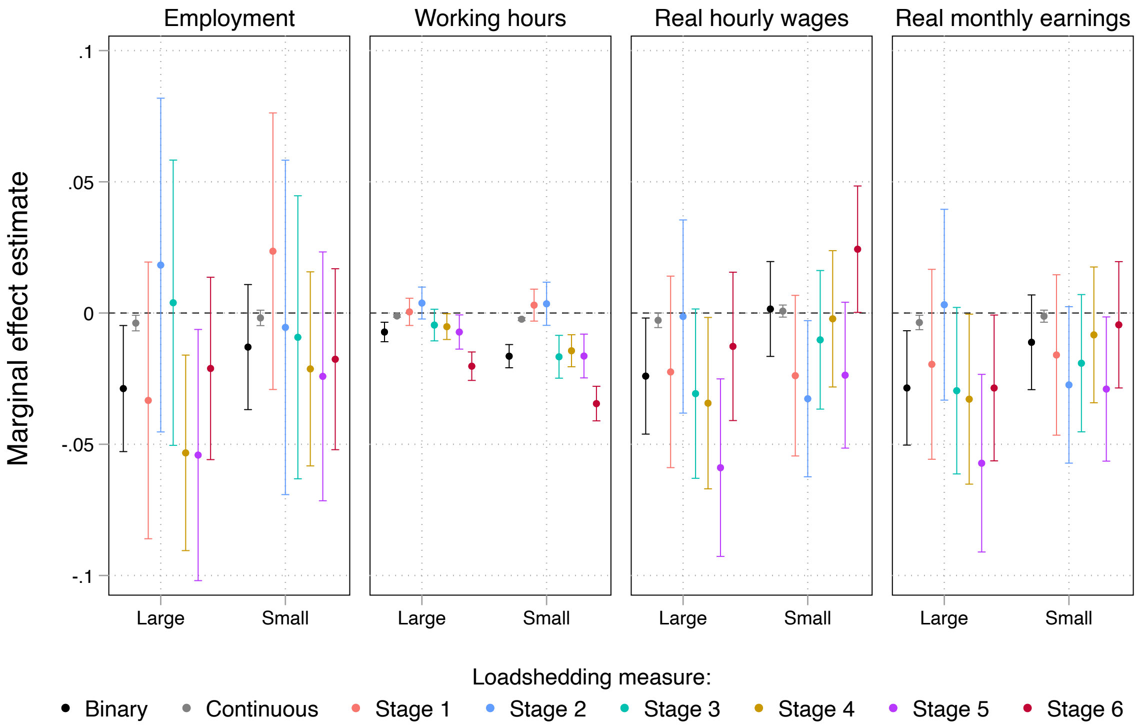
Heterogeneity by firm size

We now analyse the results of our models as per specification (2) on if and how the conditional associations between load shedding and the four outcomes of interest vary by firm size. We visually present the relevant marginal effect estimates in coefficient plots in Figure 5. Overall, we document notable heterogeneity by firm size, with workers in large firms (as defined here) exhibiting greater vulnerability to load shedding with respect to all outcomes. For workers in small firms, we only find evidence of a significant, negative, and larger association between load shedding and working hours, but no other outcome.

Regarding employment, recall as per Section 4 that the outcome is now measured as weighted employment counts on a log scale as opposed to a binary employment dummy, and as such are subject to a different interpretation. As shown in panel (a), periods of load shedding are associated with 2.9 per cent lower employment for workers in large firms, which is marginally larger than the average estimate in Table 1, while the relevant estimate for those in small firms is statistically insignificantly different from zero. This latter finding holds regardless of load shedding measure. The estimate for large firms remains significant using the continuous load shedding measure and, by load shedding intensity, for stages 4 and 5 in particular. The estimate for the highest stage is also negative but is insignificant. This suggests that employment in both small and large firms is insensitive to low levels of load shedding, consistent with our average results in the preceding section; however, higher levels are costly particularly for large firms.

This result may seem counter-intuitive, given an a priori expectation that larger firms are less vulnerable to such shocks due to, for instance, more resources and economies of scale. However, this finding of a lack of any or larger effect on small firms is not unique. Using firm-level data from 14 African countries, Cole et al. (2018) estimate negative effects of electricity outages on both small and large firms, and while the difference in these effects is not statistically significant, the magnitude of the effect on large firms is greater. What might explain this? The survey data here unfortunately does not allow one to examine possible underlying mechanisms, however the literature points to the differential input compositions across firms of varied sizes. For instance, the input composition of small firms—comprising primarily labour—is less substitutable than that of large firms, which may allow them to adjust better to power outages with respect to layoffs (Cissokho and Seck 2013; Hardy and McCasland 2021).

Figure 5: Model estimates of the heterogeneous association between load shedding and labour market outcomes, by firm size



Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. All models control for the vector of macroeconomic controls, quarter fixed effects, and a City of Cape Town district municipality dummy. Wage/earnings data privately provided by StatsSA, is only available from 2010Q1 onwards, and is adjusted for outliers and missing values. Capped spikes represent 95 per cent confidence intervals.
Source: authors' calculations based on QLFS 2008Q1–2023Q2 as well as electricity production and consumption data provided by Eskom.

Considering the intensive margin, in contrast to the employment results we estimate negative associations for both small and large firms, with a stronger association for the former. The magnitudes of these associations are smaller than those for employment, again consistent with the preceding average estimates, but are highly statistically significant. Load shedding is associated with 0.7 fewer weekly working hours in large firms, but more than double this (1.6 hours) in small firms. The magnitude of this difference holds when the continuous load shedding measure is alternatively used. Regardless of firm size, we estimate null associations for low levels of load shedding but stronger negative associations for higher levels of load shedding, consistent with the preceding average results. However, for a given level of severity these associations remain stronger for small firms. For instance, stage 6 load shedding is associated with 3.5 fewer weekly working hours for workers in small firms but 2 fewer hours for their large firm counterparts. Interestingly, the magnitude of this within-stage difference reduces for higher stages, from factors of 3.6 and 2.8 in stages 3 and 4 to 2.3 and 1.7 in stages 5 and 6.

For both real hourly wages and monthly earnings, we estimate negative associations for workers in large firms but largely not for those in small firms. For the former, periods of load shedding are associated with 2.4 per cent lower hourly wages and 2.9 per cent lower monthly earnings relative to periods when load shedding is absent. Again, larger associations are evident for higher levels of load shedding, particularly 4 to 6, while we do not find evidence of such associations for less severe levels. Together with the working hour estimates, these results imply that the lower monthly earnings of workers in large firms during periods of load shedding are driven by downward adjustments to both working hours and hourly wages. For those in smaller firms, on the other hand, we only find evidence for downward adjustments to working hours alone which do not necessarily translate into lower monthly earnings.

Heterogeneity by industry

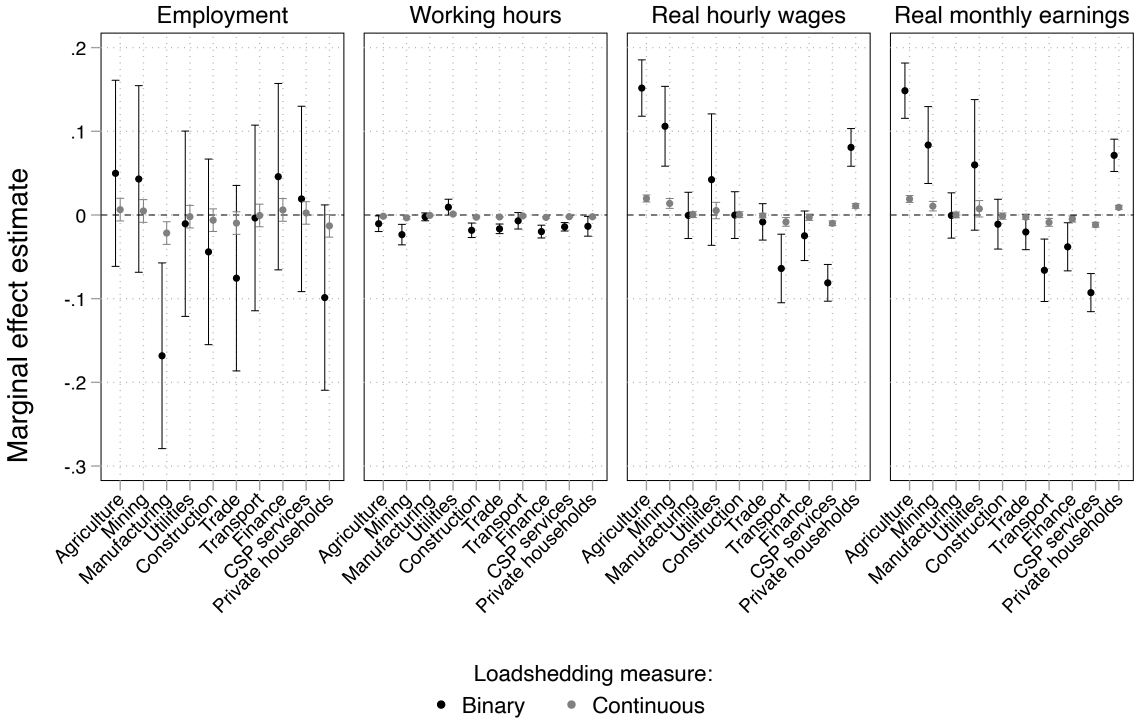
Finally, we analyse the results of our models as per specification (3) on if and how the conditional associations of interest vary by main industry of employment. As previously discussed, we would expect any negative relationship to be stronger for more energy-intensive industries; that is, industries which comprise firms whose production processes demand high amounts of electricity per unit of output. Data on industry-level energy intensity at the one-digit SIC level in South Africa is unfortunately sparse, however the literature considers agriculture, mining and quarrying, manufacturing, and construction in particular as energy-intensive industries in the country (Walsh et al. 2021, 2023). We again visually present the relevant marginal effect estimates in coefficient plots in Figure 6.[26]

Overall, our estimates are suggestive of significant cross-industry effects. On the extensive margin, the average negative employment associations we document above are driven by manufacturing. The coefficients for all other industries are statistically insignificant at conventional significance levels, while the estimated coefficient for manufacturing is notably large in magnitude and highly statistically significant: on average, load shedding periods are associated with a 16.8 per cent lower manufacturing employment relative to periods with no load shedding. This estimate is approximately 6.5 times the magnitude of the equivalent average estimate in Table 1.[27] The alternative continuous measure suggests that a 10 per cent increase in load shedding intensity is associated with a 0.2 per cent lower manufacturing employment. These concentrated effects on manufacturing are consistent with Walsh et al. (2021, 2023) and Mensah (2024), which highlight the industry's vulnerability in terms of both output and employment.

[26] For brevity we omit the marginal effect estimates with respect to load shedding stage. These results are available from the authors upon reasonable request.

[27] A 1.1 percentage point lower employment probability which, as discussed in the text, translates to 2.6 per cent using the mean employment rate in the pooled sample.

Figure 6: Model estimates of the heterogeneous association between load shedding and labour market outcomes, by main industry



Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. All models control for the vector of macroeconomic controls, quarter fixed effects, and a City of Cape Town district municipality dummy. Wage/earnings data privately provided by StatsSA, is only available from 2010Q1 onwards, and is adjusted for outliers and missing values. Capped spikes represent 95 per cent confidence intervals.
Source: authors' calculations based on QLFS 2008Q1–2023Q2 as well as electricity production and consumption data provided by Eskom.

Considering the intensive margin, in contrast to employment we estimate significant negative associations with respect to working hours for most industries. Manufacturing, utilities, and transport and communication serve as the exceptions whose coefficients do not statistically differ from zero. Using the binary measure, the estimates range from -0.010 for agriculture to -0.024 for mining and quarrying, implying that load shedding periods are associated with downward working hour adjustments from 1 to 2.4 per cent per week, or up to over 10 per cent per month on average. This latter estimate is approximately double the average estimate as per Table 2. On the other hand, the hourly wage and monthly earnings estimates are mixed. For the former, the estimates tend to be insignificant from zero, while for the latter, the largest share are negative. The few positive estimates may be driven by a composition effect, as discussed earlier, or alternatively may be explained by employers offering workers higher wages per hour worked to compensate for working fewer hours. These hypotheses are of course merely speculative and thus inconclusive, and thus a more thorough analysis is required to adequately determine the underlying mechanisms.

6 Robustness tests

In this section we present the results of two robustness tests which seek to test the sensitivity of our main results. We first account for the most recent load shedding period coinciding with the COVID-19 pandemic. As discussed earlier, pandemic-induced variation in our outcomes of interest coupled with the more frequent and severe load shedding episodes during the period may confound our estimated relationships of interest. To address this, we re-estimate two variations of specification (1) using either a stratified sample which excludes all observations from 2020Q2, 2021Q1, and 2021Q3, or the full sample but include a binary dummy variable set equal to one for all observations in these survey waves and zero otherwise. The justification for these specific periods includes the pandemic's onset in the country at the end of March 2020, the initial lockdown period during 2020Q2, and the re-implementation of stringent restrictions following subsequent infection waves in 2021Q1 and 2021Q3.[28] For brevity, we present the results in Table 5 with respect to the binary and continuous load shedding measures alone. The estimates are very similar to the estimates presented in Tables 1 to 4. The employment coefficients are marginally smaller (18 per cent) relative to our main results, but the coefficients are not statistically significantly different from one another and exhibit the same sign and level of significance. On the intensive margin, all estimates are similar to those using our main specification with respect to magnitude, sign, and level of significance. Overall, these results imply that our results are not driven by the dynamics of the labour market during the pandemic.

[28] We avoid selecting the whole pandemic period from the end of March 2020 through to June 2022 when all remaining pandemic-related restrictions were repealed because doing so would account for a large share of variation in load shedding incidence and severity.

Table 5: Model estimates after controlling for the COVID-19 pandemic period

	(1) Stratified	(2) Pandemic dummy	(3) Stratified	(4) Pandemic dummy	(5) Stratified	(6) Pandemic dummy	(7) Stratified	(8) Pandemic dummy
	Pr(employment)				Log(working hours)			
Load shedding measure:								
(i) Binary	-0.009***	-0.008***			-0.014***	-0.011***		
	(0.002)	(0.002)			(0.002)	(0.001)		
(ii) Continuous			-0.001***	-0.001***			-0.002***	-0.002***
			(0.000)	(0.000)			(0.000)	(0.000)
Constant	0.461***	0.444***	0.450***	0.432***	3.961***	3.928***	3.952***	3.918***
	(0.026)	(0.024)	(0.026)	(0.024)	(0.020)	(0.019)	(0.020)	(0.019)
Observations	2771378	2856719	2771378	2856719	1107621	1136749	1107621	1136749
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Log(real hourly wage)				Log(real monthly earnings)			
Load shedding measure:								
(i) Binary	-0.007	-0.008			-0.017**	-0.017**		
	(0.008)	(0.008)			(0.008)	(0.008)		
(ii) Continuous			-0.001	-0.001			-0.002*	-0.002**
			(0.001)	(0.001)			(0.001)	(0.001)
Constant	3.605***	3.665***	3.621***	3.682***	9.087***	9.085***	9.088***	9.085***
	(0.133)	(0.120)	(0.133)	(0.120)	(0.134)	(0.120)	(0.134)	(0.121)
Observations	860 420	889 148	860 420	889 148	860 428	889 156	860 428	889 156

Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. All models control for the vector of macroeconomic controls, a City of Cape Town district municipality dummy, and quarter fixed effects. Stratified models exclude observations from 2020Q2, 2021Q1, and 2021Q3. 'Dummy control' refers to the inclusion of a dummy variable equal to one for observations in 2020Q2, 2021Q1, and 2021Q3 and zero otherwise. Standard errors presented in parentheses. *** p<0.01; ** p<0.05; * p<0.10.
Source: authors' calculations based on QLFS 2008Q1–2023Q2 as welle as electricity production and consumption data provided by Eskom.

We next analyse the sensitivity of our results with respect to our chosen measures of load shedding. Recall that our covariates of interest are measured using MLR which, as described in Section 3, is not observed but instead estimated by Eskom based on the difference between the national day-ahead demand forecast and actual demand while load shedding is in place. As an alternative measure, we make use of observed data on both electricity supply and demand to measure electricity shortage, as used in Figure 2, defined as electricity demand less supply. Again, demand is measured as the daily peak in the hourly average demand that needs to be supplied by all resources that Eskom has contracts with, while supply is measured as the total available capacity available from all generation resources that Eskom has contracts with at the daily demand peak. Because data on these variables are only available from 2016Q3 onwards, the sample is restricted accordingly to observations between 2016Q3 and 2023Q2 inclusive. Consequently, the resultant estimates are not strictly comparable to our main results which use the full sample, but are still useful given the greater incidence and severity of load shedding within this period. We re-estimate specification (1) using two variants of this measure: a binary variable set equal to one when a shortage is experienced and zero otherwise, and a continuous variable indicating the severity of the shortage as a share of demand. The results are presented in Table 6 and are strongly consistent with our main results. The estimates using the binary indicator are all larger than those in our main results, but are the same in sign and are all highly significant, apart from the hourly wage results which are null. This latter finding is again in line with our main results. Overall, these estimates show that our main results are not attributable to our primary measure of load shedding.

Table 6: Model estimates using alternative load shedding measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(employment)		Log(working hours)		Log(real hourly wage)		Log(real monthly earnings)	
Shortage (binary)	-0.041***		-0.043***		0.049***		0.007	
	(0.004)		(0.004)		(0.015)		(0.015)	
Shortage (% of demand)		-0.002***		-0.002***		0.002***		0.000
		(0.000)		(0.000)		(0.001)		(0.001)
Constant	0.263***	0.113***	3.607***	3.418***	4.328***	4.508***	9.404***	9.401***
	(0.027)	(0.030)	(0.036)	(0.041)	(0.118)	(0.134)	(0.117)	(0.133)
Observations	1 077 594	1 077 594	423 315	423 315	414 984	414 984	414 988	414 988
R^2	0.007	0.007	0.002	0.002	0.006	0.006	0.006	0.006

Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. Shortage refers to electricity demand less supply, where demand is measured as the daily peak in the hourly average demand that needs to be supplied by all resources that Eskom has contracts with, and supply is measured as the total capacity available from all generation resources that Eskom has contracts with at the daily demand peak, including non-commercial units and renewables. All models control for the vector of macroeconomic controls, a City of Cape Town district municipality dummy, and quarter fixed effects. Standard errors presented in parentheses. *** p<0.01; ** p<0.05; * p<0.10.
Source: authors'calculations based on QLFS 2016Q3–2023Q2 as well as electricity production and consumption data provided by Eskom.

7 Conclusion

Electricity access has greatly improved in many developing countries in recent decades, however supply is often characterized by frequent outages which are expected to significantly hinder the benefits of expanded access. While existing studies document the adverse effects of electricity outages on various economic outcomes, almost none consider labour market effects. This study contributes to this relatively sparse literature in the context of South Africa, a middle-income country characterized by extreme unemployment and systemic power supply issues referred to as load shedding, which have increased in incidence and intensity in recent years. We merge labour force survey data with macroeconomic data and high-frequency electricity production and consumption data from 2008 to 2023 and exploit temporal variation in the incidence and intensity of outages to estimate average and heterogenous associations with employment, working hours, hourly wages, and monthly earnings.

We find that, on average, periods of load shedding are associated with a 2.6 per cent lower employment probability, 1.3 per cent fewer working hours per week, and 1.7 per cent lower real monthly earnings. A null association with hourly wages suggests these monthly earnings reductions are driven by working hour reductions. All these average associations are however not evident for lower levels of load shedding but tend to increase with load shedding intensity, exceeding double the size of the average association for high levels. We document notable heterogeneity with respect to firm size and industry. Workers in large firms exhibit vulnerability with respect to all outcomes, while only negative but larger working hour adjustments are evident for small firms. A strong, negative employment association for the manufacturing industry drives the average association, while most industries exhibit downward working hour adjustments of up to 10 per cent per month. Industry-specific estimates for wages and earnings are however mixed. These results are neither explained by seasonality nor temporal variation in macroeconomic conditions, and are robust to alternative load shedding measures and accounting for labour market dynamics during the pandemic period.

Overall, our analysis provides evidence of the negative effects of electricity outages on labour market outcomes in developing countries. In South Africa in particular, it suggests that the labour market is largely insensitive to relatively low levels of load shedding; however, high levels are particularly costly. Importantly, these former null estimates do not imply that low levels of load shedding do not cause any adversity in the economy and should be tolerated. The adoption of self-generation mitigation measures may partially explain this result, however low levels of load shedding still incur costs elsewhere. This is consistent with the negative effects on several non-labour market outcomes examined in the literature which do not form part of this study's focus. For higher levels of load shedding, the negative relationships we estimate hold on both the extensive and intensive margins, but larger adjustments to the former threaten efforts to bolster job creation and preservation in a country already characterised by extreme unemployment. This highlights the urgent need for policy-makers to reduce the frequency and intensity of these outages and, of course, eventually eliminate them. Finally, while this analysis provides, to our knowledge, the first set of estimates of the relationships between these outages and labour market outcomes in South Africa, we stress that they are descriptive in nature. Our empirical strategy does not allow us to confidently infer causality. Instead, it is intended to provide an evidence base to begin to fill the gap in the literature.

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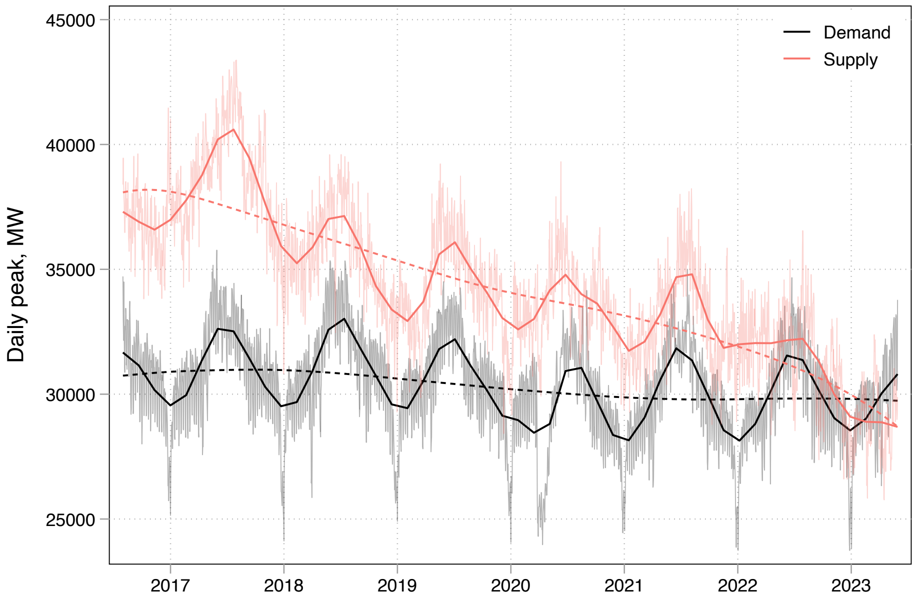
Appendix

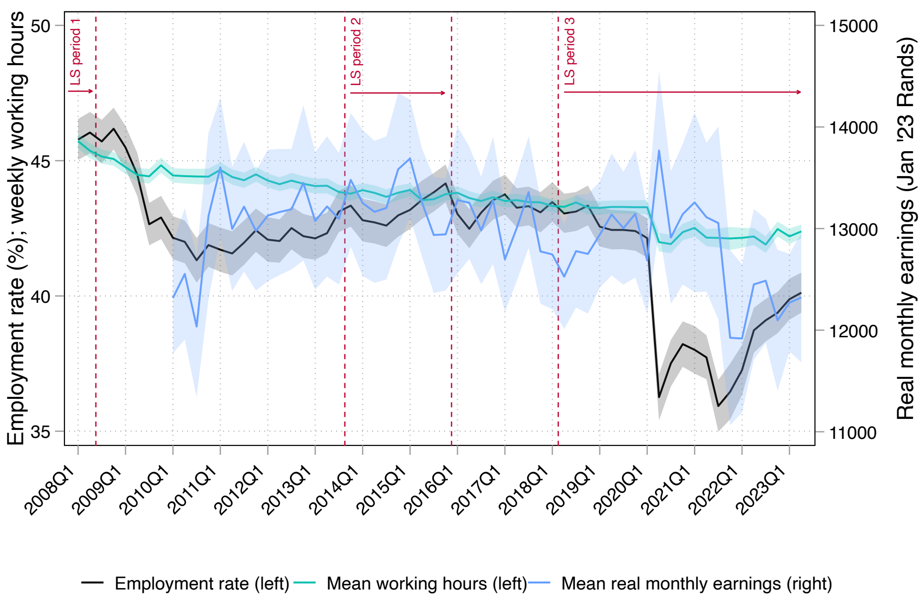
Figure A1: Electricity supply and demand in South Africa, 2017–23



Note: demand is measured as the daily peak in the hourly average demand that needs to be supplied by all resources that Eskom has contracts with, and supply is measured as the total capacity available from all generation resources that Eskom has contracts with at the daily demand peak, including non-commercial units and renewables.

Source: authors' calculations based on electricity production and consumption data provided by Eskom.

Figure A2: Trends in employment, working hours, and real monthly earnings in South Africa, 2008Q1–2023Q2



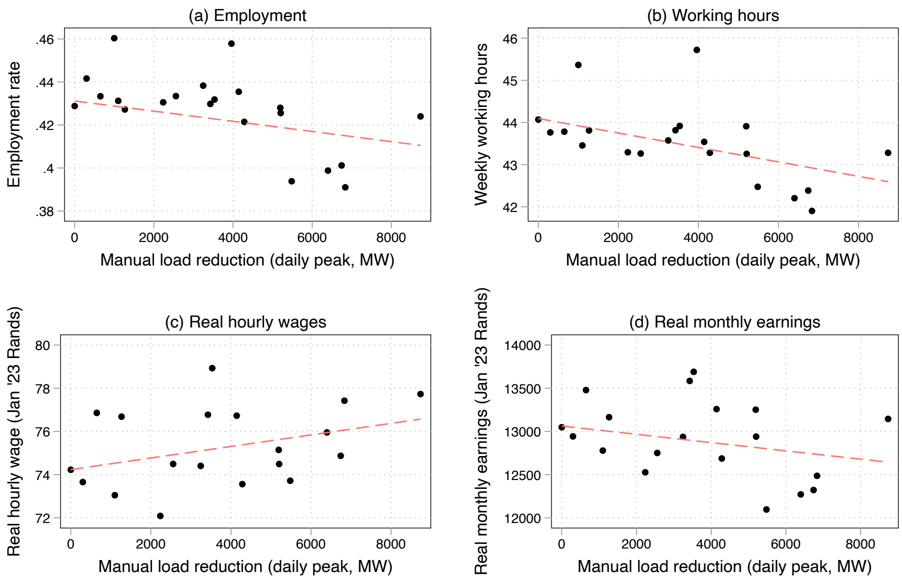
Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. Earnings data privately provided by StatsSA, is only available from 2010Q1 onwards, and is adjusted for outliers and missing values. Shaded areas represent 95 per cent confidence intervals. Vertical reference lines represent distinct periods when load shedding (LS) was in place.

Source: authors' calculations based on QLFS 2008Q1–2023Q2.

Figure A3: Binned scatterplot of load shedding against employment counts in South Africa

Note: sample restricted to those of working age (15–64 years). Estimates weighted using sampling weights and account for the complex survey design. Wage and earnings data privately provided by StatsSA, is only available from 2010Q1 onwards, and is adjusted for outliers and missing values. Each plot uses 50 equal-sized bins of the variable on the horizontal axis.
Source: authors' calculations based on QLFS 2008Q1–2023Q2 as welle as electricity production and consumption data provided by Eskom.

Figure A4: Binned scatterplots of load shedding against labour market outcomes in South Africa, omitting the COVID-19 pandemic period



Note: sample restricted to those of working age (15–64 years). Data from 2020Q2 to 2022Q2 inclusive are omitted. Estimates weighted using sampling weights and account for the complex survey design. Wage and earnings data privately provided by StatsSA, is only available from 2010Q1 onwards, and is adjusted for outliers and missing values. Each plot uses 50 equal-sized bins of the variable on the horizontal axis.
Source: authors' calculations based on QLFS 2008Q1–2020Q1 and 2022Q3–2023Q2 as well as electricity production and consumption data provided by Eskom.