How do jobseekers respond to weather shocks?

Evidence from South Africa

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March 31, 2022

Abstract

I study how weather shocks affect job search behavior. I combine daily temperature data with a survey from South Africa that includes detailed information on the methods unemployed individuals used to look for a job and their expectations about finding a job. I estimate that a 1-degree increase in the mean temperature over the month leading to the survey date increases the number of channels jobseekers use to look for a job by 1.8%. Higher temperatures increase the use of methods not employed frequently to look for work and the probability that a jobseeker will take steps towards starting their own business. I do not observe a significant change in the amount of money used to look for work, suggesting that higher temperatures induce jobseekers to diversify the channels through which they look for work and to consider switching to self-employment.

JEL Classification: J64, Q54, O55

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1 Introduction

It is clear by now that weather fluctuations (and particularly extreme weather events) can negatively affect labor productivity (Somanathan et al., 2021), and therefore output (Taraz, 2018) and employment Colmer (2021). If weather shocks and higher temperatures require workers to relocate to less vulnerable sectors, it is important to study whether those affected are taking the necessary steps to find a new job. Yet, we know very little about how weather events affects jobseekers' strategies to find employment.

This paper aims to fill this gap by studying how temperature affects job search behavior using individual-level data from South Africa, one of the countries with the highest unemployment rates in the world (World Bank, 2021). I combine survey data about job search from jobseekers with high-resolution and detailed meteorological data to estimate the effect of higher average temperature on job search behavior, proxied by the number of methods used to look for work, the amount of money spent looking for work, and the expectations of finding a job.

I find that higher temperatures lead jobseekers to use more methods to look for work. The number of job search methods used in the four weeks to the survey increase by 1.8% for a one-degree Celsius increase in the average temperature during that time frame. The increase is relatively larger for methods used least frequently and for taking steps towards starting their own business. I can rule out that this effect is driven by changes in the composition of the unemployed pool, be it through movements in and out of the labor force, employment, or survey attrition.

I also find that higher temperatures slightly reduce jobseekers' confidence of being able to find work, in line with previous studies which show a reduction in employment (Jessoe et al., 2018; Ibánez et al., 2021; Taraz et al., 2021). However, I do not observe a significant change in the amount of money used to look for work. Together with the results on search methods, this suggests that higher temperatures do not induce jobseekers to increase their search effort (i.e. the resources used to look for work), but rather to diversify the channels through which they look for work and to consider switching to self-employment.

I then investigate whether there are differences in the effect that temperature has on job search across the unemployed. Conditional quantile regressions show that the effect of a one-degree increase in the average temperature in the four weeks to the survey is more than twice as high for those in the 90th decile of the job search distribution compared to those in the 10th decile. This indicates that individuals more engaged in the process of looking for work react more to changes in the environment. If these changes in behavior lead to higher chances of finding a job, jobseekers exerting lower search effort may benefit from information campaigns about alternative ways to look for work and job search planning, as shown by Abel et al. (2019).

This paper contributes to the burgeoning literature investigating the effects of weather conditions in general (and climate change in particular) in the labor market (Dell et al., 2014). First, studies have shown that climate change reduces agricultural output, despite farmers' efforts to adapt to a changing environment (Burke & Emerick, 2016; Taraz, 2018; Aragón et al., 2021). Colmer (2021) shows that these changes in turn reduce labor demand and wages in the agricultural sector, so workers depend on the ability of other economic sectors to absorb them in order to soften the effect of weather shocks on unemployment. However, recent studies show that higher temperatures reduce worker productivity (Adhvaryu et al., 2020; Somanathan et al., 2021) and time worked (Graff Zivin & Neidell, 2014) in factories. Moreover, hotter weather increases workplace injuries both in outdoor activities and indoor, low-wage sectors (Dillender, 2019; Park et al., 2021), thus increasing inequality across workers.

Despite these advances in the field, little attention has been given to the study of how climate change affects the way in which jobseekers look for work, with the only exception of González Chapela (2021). However, this paper differs from his in several ways: first, I study the channels used by jobseekers to look for work rather than the time they spend looking for work. While the first is related to the strategy used by jobseekers, the second relates to search effort. Secondly, I do so over a longer period of time (30 days vs. one day), thus being able to capture more persistent effects of weather fluctuations. Finally, the contexts in which these two studies are carried out could not be more different: while the US is a developed country with a dynamic labor market and relatively low unemployment rate, South Africa is a developing economy with one of the highest unemployment rates in the world. Hence, we may expect differences in the effects of weather conditions on job search between the two countries.

In addition, this paper contributes to the study of job search behavior by the unemployed. The availability of longitudinal and high-frequency surveys in the last decade have allowed researchers to study how economic shocks and the design of insurance mechanisms such as unemployment benefits affect search effort and intensity (Faberman & Kudlyak, 2019; Marinescu et al., 2020), and the formation and evolution of reservation wages over the unemployment spell (Krueger & Mueller, 2016; Marinescu & Skandalis, 2020; Mueller et al., 2021). In addition, scholars have conducted experiments to study the impact of providing job search assistance (Belot et al., 2018) and planning (Abel et al., 2019) on the strategies used by jobseekers and their success in finding work. I complement the existing literature by studying how local and short-term shocks affect the strategies used by jobseekers in a country with a narrow unemployment insurance system (Leibbrandt et al., 2010).

The rest of the paper is structured as follows: the next section describes the various sources of data used and the empirical strategy implemented. Section 3 presents the main results, as well as robustness checks and an examination of heterogeneous treatment effects. Finally, Section 4 concludes.

2 Data and empirical strategy

2.1 Job search data

I use individual data on job search activities from South Africa's National Income Dynamics Study (NIDS). NIDS is a longitudinal survey that collects demographic and socio-economic information from a nationally representative sample of individuals every two years beginning in 2008. Geographically, the the data is available at the district level, the second administrative division of South Africa. The survey uses the district boundaries resulting from the 2011 census, with 52 districts (44 district municipalities and 8 metropolitan municipalities). I use the five waves that are currently available, spanning the period 2008-2017. The data includes the exact interview date of each respondent, allowing me to merge it with the weather data at the daily level.

Job search information consists of a series of questions regarding whether the respondent used a series of methods to look for a job in the four weeks up to the survey date, the amount of money spent on travel costs associated with job search in the week up to the survey date, and the stated likelihood that respondents will find a job in the future (from one month up to two years). I aggregate the information about methods to look for work in the four weeks to the survey to create a variable for search intensity. Similarly, I create a measure of the perceived likelihood of finding a job within two years by aggregating the multiple questions about the probability that the respondent will find a job.

I consider only individuals aged 15 or over since this is the legal age to work in South Africa.[1] Unemployed individuals are those who were not working at the time of the survey but were willing to work at any point in the four weeks up to the survey. This includes those considered "discouraged" because they are not actively looking for a job. This broader definition of unemployment is justified by the high and persistent unemployment in South

[1]While the adult module of the survey is targeted at those 15 or more, a few respondents are less than 15 based on their date of birth and the survey date. Results do not change if I include these individuals in the analysis

Africa. Moreover, a number of studies have shown that in South Africa, the “non-searching” unemployed are more similar to the “searching” unemployed than to the inactive in terms of their characteristics and future outcomes (Kingdon & Knight, 2006; Lloyd & Leibbrandt, 2014; Posel et al., 2014). On the other hand, a person is not in the labor force if they are not working and they were not willing to work in the four weeks up to the survey.

The final sample is composed of 94,715 observations which correspond to individuals aged 15 or more in a given wave. Of these, 48,218 correspond to individuals-wave in the labor force, 12,912 of which are not employed but are willing to work to work in the four weeks up to the survey. Table 1 presents summary statistics for the sample of unemployed individuals.

2.2 Weather data

I use daily temperature data from the Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2), produced by NASA Global Modeling and Assimilation Office (GMAO). The dataset provides global climate metrics on a 0.5-by-0.5 degree resolution from 1980 onwards.

I match each grid within the boundaries of South Africa to a district by calculating its distance to each district's centroid and finding the one closest to it. I then average the daily mean temperature within districts to construct a measure of the daily average temperature recorded for each district. Because most questions about job search make reference to a period of one week or one month to the survey date, with this information I calculate, for each day, the mean temperature in the previous seven and 30 days.

Summary statistics of these variables across districts and survey dates can be found in Table 1. In addition, Figure 1 shows the average temperature for each district during summer (January to March) and winter (July to September) months. While at the national level average temperatures are mild at about 18ºC, there is large variation both across space and time, with some districts experiencing average temperatures of 27ºC in summer months.

2.3 Empirical strategy

To study how changes in temperature affect job search behavior, I estimate equations of the following form:

$$y_{imd} = \alpha + \beta Temp_{md} + \Gamma X_i + \mu_m + \Theta_d + \varepsilon_{imd} \tag{1}$$

where y_{imd} is the outcome of interest for individual i from district m surveyed at date d. $Temp_{mdy}$ is the average temperature in the days up to the survey referenced in the dependent variable (7 or 30 days). I include a set of individual controls X_i (gender, polynomials of degree two on age and education, ethnicity, marital status, household size, household income and length of unemployment), location fixed effects μ_m and a set of date fixed effects Θ_d (month, year and month-by-year). In all regressions, standard errors are clustered at the district level to account for spatial correlation.

The identification strategy relies on the quasi-random nature of temperature with respect to the date in which the survey is conducted. In other words, my identifying assumption is that that temperature does not interfere with the rollout of the survey. This is unlikely given the time involved in preparing the field work of each survey and the efforts made to track respondents over time (Leibbrandt et al., 2009).

To check whether this assumption holds, Table 2 shows the relationship between the number of interviews conducted and the average temperature on the same date, the previous week and the previous month. Column 1 shows that there is no relationship between the number of interviews conducted in one day and the temperature for that day.

On the other hand, there is a statistically significant relationship between the number of surveys in a day and the average temperature in the previous week (Column 2) and the previous month (Column 3). However, this relationship is positive and small in magnitude: an additional degree Celsius in the average temperature of the previous week (month) leads to an increase in surveys of 0.67% (0.90%). In addition, despite the increase in surveys, in

Table A1 I show that the characteristics of unemployed respondents bear no relationship to the average temperature in the previous month.

3 Results

The main results are presented in Table 3. Columns 1 and 2 show that changes in the temperature in the 30 days to the survey have no impact on either labor force participation or unemployed. This means that changes in temperature do not alter the composition of the unemployed group, which could affect the internal validity of the job search estimates. While this contrasts with other studies that look at the effect of higher temperatures on employment, the key difference is that I focus on a shorter window of time over which the pool of unemployed is unlikely to change significantly.

Column 3 of Table 3 shows that a one-degree Celsius increase in the average temperature in the 30 days to the survey causes an increase of 0.032 in the number of methods used to look for a job, or 1.8% with respect to the mean. Considering that the average temperature in South Africa for the period is 17.88 ºC, the results translate into an elasticity of 0.31. On the other hand, column 4 shows no change in the amount of money spent looking for a job, which may indicate that jobseekers are simply allocating their resources into more means to find work. Consistent with this, I find that higher temperatures produce a significant but small reduction in jobseekers' confidence of finding work within 2 years (column 5).

In Table 4, I show the results of the effect of temperature on each specific way in which jobseekers could have looked for work in the four weeks up to the survey.[2] For a one-degree increase in the average temperature jobseekers are 8.3% more likely to look for work by registering at an employment agency and 13.7% more likely to use other methods not listed in the survey; they are also 1.8% more likely to seek assistance from relatives or friends.

In addition to looking for wage employment, when average temperatures increase by one

[2]Because of the large number of regressions, I control for the Familywise error rate (FWER) using Westfall & Young step-down procedure (Westfall & Young, 1993) implemented by Jones et al. (2019).

degree Celsius, jobseekers are 8% more likely to look for land, building, equipment or applied for a permit to start their own business or farming. This may be related to the reduction in jobseekers' perceived probability to find wage employment shown in column 5 of Table 3.

To summarize, while higher temperatures do not increase the probability of becoming unemployed or dropping out of the labor force, they induce those unemployed to employ less used methods to look for work (only 13.3% of jobseekers went to an employment agency and 0.7% used alternative methods), and to take actions to start a new business. Even though I do not observe a reduction in any job search channel, there is also no change in the travel expenses incurred to look for work. Together with the lower perceived probability of finding work, this suggests that temperature increases leads to diversification of jobseekers' search strategy and to switching their focus from wage employment to self-employment.

3.1 Robustness checks

Longitudinal surveys such as NIDS may suffer from attrition. If attrition among the unemployed is related to weather events such as higher temperatures or their search effort, then the results shown previously could be biased. I investigate whether this is a possibility by looking at the determinants of attrition among survey respondents.

The results can be found in Table A2, where the dependent variable is an indicator that takes the value of one if an individual was surveyed in a given round but was not surveyed in the round immediately following. I consider for this analysis rounds one to four of the survey. Because survey rounds are approximately two years apart from each other, to capture the effect of weather on attrition I consider the average temperature in the two years after an interview took place.

Average temperature in the two years after a survey does not seem to affect the probability of being resurveyed. Similarly, neither search effort (proxied by the number of methods used to look for work) nor the expectations to find work within two years are related to survey attrition. Even though money spent to look for work seems to be positively related with the probability of no being surveyed two years later, the coefficient is virtually zero.

Another way in which temperature or job search could affect the pool of unemployed individuals is through migration. Previous studies have found migration, both internal (Dillon et al., 2011; Hornbeck & Naidu, 2014; Baez et al., 2017) and international (Halliday, 2006; Gray & Bilsborrow, 2013; Ibánez et al., 2021) to be affected by weather conditions. If migration affects the way jobseekers look for work, or if they displace "natives" in the destination labor market (Kleemans & Magruder, 2018), the results shown above would be confounding the effect of temperature on job search behavior with that of migration.

As an additional robustness check, Table A3 shows that higher temperatures at the origin do not increase an individual's likelihood to move to a different district council. This is true regardless of the length of time considered, be it one, six or twelve months before the time of the survey.

3.2 Heterogeneity analysis

While average treatment effects point towards sizeable effects of temperature increases on job search behavior, it is interesting to figure out if these results mask heterogeneous effects across individuals or groups based on their location and socio-demographic characteristics.

I first look at the effect of higher temperature on the number of methods used to look for work for different quantiles of the distribution of this outcome. Figure 2 shows that temperature has an increasing and monotonic effect across quantiles of job search intensity. The point estimate for the 95th quantile (0.050) is actually more than twice of that of the 5th quantile (0.019). Moreover, I cannot reject that the latter is different from zero. These results imply that jobseekers with higher labor market attachment are more likely to react to changes in labor market conditions.

I then turn the attention to heterogeneous effects by gender. Women are less likely than men to participate in the labor force (46.2% of women vs. 57.6% of men are working or looking for work), they use on average fewer methods to look for work (1.73 vs. 1.98) and spend less money looking for work (78 ZAR vs. 96 ZAR per week). Given the quantile treatment effects results showing a larger effect among those with higher search intensity, one would expect the impacts to differ by gender. However, the estimates, presented in Table 5, show no differences between men and women with regards to the effect of temperature on job search behavior.

In turn, in Table 6 I look at differential effects by ethnicity. Even though unemployment rates are significantly higher among Africans (or blacks) compared to other groups (mainly Whites and Asians), I do not find any statistically significant difference of the effect of temperature on job search across these groups. The point estimate on search intensity among Africans is less than half that of other groups (0.025 vs. 0.054), and that of the percent change in the amount of money spent looking for work is about 5 times smaller (0.015 vs 0.077) but the differences are not statistically different from zero. These results suggests that Africans may benefit relatively more from policies aimed at improving job search effectiveness (such as those evaluated by Abel et al., 2019), especially in a world of rising temperatures.

Finally, I look at effects by level of education. I split the sample between those who have completed basic education (Grades 0 through 9) and those who have not. The results, presented in Table 7 show no significant differences between the these two groups, although individuals who have not completed basic education increase their search intensity as a consequence of higher temperatures slightly more than those with basic education or more (the point estimate are 0.043 and 0.03, respectively).

4 Conclusion

In the last decades, scholars have extensively studied the effect of weather conditions on human behavior. By now it is clear that higher temperatures negatively affects productivity, employment, and ultimately earnings. This is especially concerning in developing countries, where a large proportion of the workforce is employed in sectors vulnerable to weather conditions and have a lower capacity to adapt to its changes. One way to do this is by relocating to sectors less affected by weather conditions, but this could mean changing the way they look for work. However, the effect that weather fluctuations could have on job search behavior has so far been overlooked.

In this paper, I study how weather conditions affect job search behavior among the unemployed in a developing country setting such as South Africa. This is a particularly interesting context to study this phenomenon, since the country suffers from very high and persistent unemployment, and is expected to be severely affected by climate change (Ziervogel et al., 2014).

I find that higher temperatures cause an increase in search effort among the unemployed, proxied by the number of methods they use to look for work. This is mostly driven by the increase in usage of methods not typically utilized to look for work and by taking steps towards self-employment. On the other hand, jobseekers do not spend more money looking for work, which suggests that they are diversifying their job search strategies as a response to climate change. Finally, I observe a small reduction in the expectation of finding a job in the medium term as a consequence of higher average temperature, which could explain why some jobseekers shift towards self employment.

Even though I do not find significant differences in job search behavior across gender, ethnical or educational groups, conditional quantile regressions show large differences in the effect of temperature by job search intensity. Individuals who use more methods to look for a job (and are thus presumably more engaged in job search) are about twice as sensitive to an increase in temperature than those who use fewer search methods.

Considering that climate change will continue and intensify in the next decades (IPCC, 2018), the results described above suggest that jobseekers may have to change the ways they look for work. In light of this, policies aiming at counseling jobseekers about how to find work and matching them with firms are of outmost importance.

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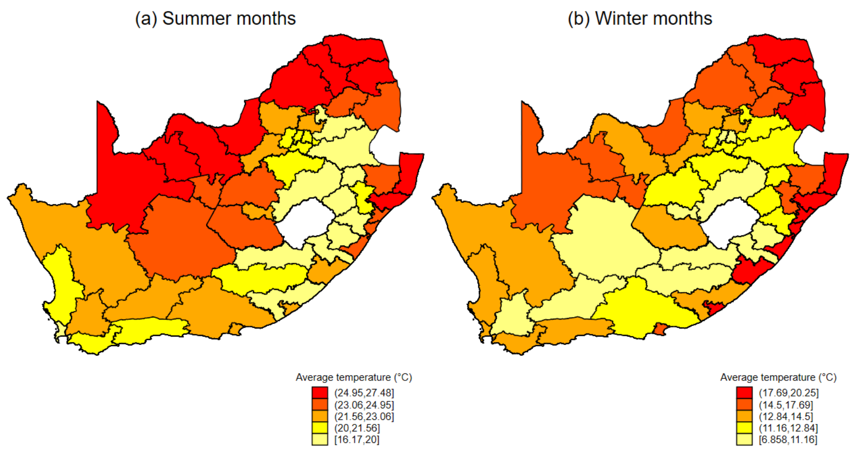
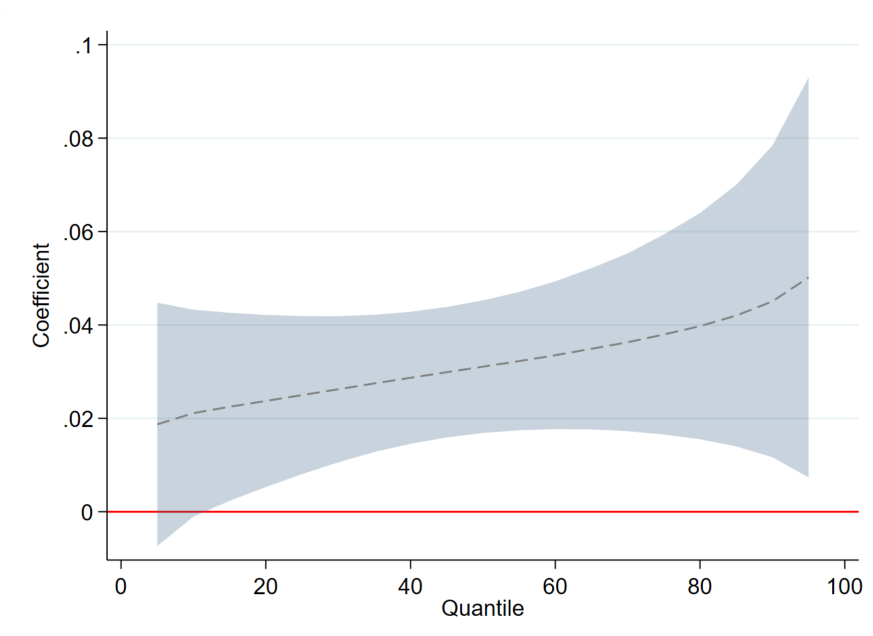
Figures and Tables

Figure 1: Average temperature per district over 30 days



Note: Panel (a) shows quintiles of the average temperature in each district in summer months (January to March) over a period of 30 days, using data from the dates in which jobseekers where interviewed. Panel (b) replicates the analysis for the winter months (July-September).

Figure 2: Quantile regression estimates of the effect of temperature on job search intensity



Note: The figure plots the estimates of the quantile regressions of the number of methods used to look for a job on the average temperature in the 30 days prior to the survey. Estimates correspond to quantiles 5 to 95 in steps of 5.

Table 1: Summary statistics

	Mean	SD	Observations
Demographic and socioeconomic characteristics			
Share male	0.38	0.48	12912
Age (years)	30.96	10.43	12912
Share African	0.86	0.35	12912
Share Coloured	0.12	0.32	12912
Share Asian or Indian	0.01	0.08	12912
Share White	0.01	0.11	12912
Share married	0.25	0.43	12912
Household size	6.02	3.54	12912
Share living in urban areas	0.49	0.50	12912
Years of education	9.52	2.94	12912
Completed basic education (share)	0.63	0.48	12912
Household income (2008 ZAR)	3133	4686	12912
Job search characteristics			
Months looking for a job	39.31	51.48	12912
Methods used to look for a job	1.82	1.43	12912
Likely to find a job within 2 years (share)	0.90	0.30	10277
Likely to find a job in 1 month (share)	0.25	0.43	10138
Likely to find a job in 3 months (share)	0.26	0.44	6411
Likely to find a job in 6 months (share)	0.40	0.49	5919
Likely to find a job in 1 year (share)	0.55	0.50	3711
Likely to find a job in 2 years (share)	0.38	0.49	1721
Weather characteristics			
Average temperature in the previous 30 days (º C)	17.88	4.76	7139
Average temperature in the previous 7 days (º C)	17.75	4.99	7139

Note: Panels 1 and 2 show the mean and standard deviation of demographic, socioeconomic, and job search variables for the sample of interest. The sample is composed of individuals aged 15 or more who do not have a job at the time of the interview but are willing to work. Panel 3 corresponds to the mean temperature (in degrees Celsius) in the 30 and 7 days prior to each survey across South Africa. In Panel 3, each observation corresponds to a district-date.

Table 2: Effect of temperature on the number of surveys conducted

	(1) Surveys	(2) Surveys	(3) Surveys
Temperature on same date	0.110		
	(0.076)		
Temperature in previous week		0.295***	
		(0.103)	
Temperature in previous month			0.391***
			(0.107)
Observations	42,160	42,160	42,160
R^2	0.556	0.556	0.556
Dependent variable mean	43.68	43.68	43.68
Individual controls	Yes	Yes	Yes
District FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes
Year-by-month FEs	Yes	Yes	Yes

Note: The dependent variable is the number of surveys conducted during the day. The variables of interest are the average temperature (in ºC) in the district on the same day (row 1), in the previous week (row 2) and in the previous month (row 3) of the survey date. The sample includes all respondents aged 15 and over who appeared in a previous wave and who were not working at the time of the survey but were willing to work at any point in the four weeks up to the survey. Individual controls include gender, polynomials of degree 2 of age and education, ethnicity, household size, marital status, household income and months spent looking for a job. Standard errors clustered at the district level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Effect of temperature on unemployment and search behavior

	(1) Labor force participation	(2) Unemployed	(3) Search methods	(4) Money spent to look for work	(5) Likely to find a job within 2 years
Average temperature	-0.000	0.001	0.032***	0.020	-0.004**
	(0.002)	(0.002)	(0.011)	(0.019)	(0.002)
Observations	94,715	48,218	12,912	10,550	10,277
R^2	0.286	0.167	0.243	0.141	0.146
Dependent variable mean	0.509	0.280	1.822	84.71	0.897
Individual controls	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes
Year-by-month FEs	Yes	Yes	Yes	Yes	Yes

Note: Dependent variables are indicators for participation in the labor force and unemployment (columns 1 and 2), the number of methods used to look for a job in the four weeks to the survey (column 3), the amount of money spent on transportation in the seven days to the survey to look for work (column 4, measured in South Africa Rand of 2008), and the stated probability of finding a job within two years (column 5). The variable of interest is the average temperature (in º C) in the district in the 30 days to the survey date (7 days in the case of column 4). In column 1 the sample corresponds to all respondents aged 15 and over. In column 2 the sample includes all respondents aged 15 and over in the labor force. In columns 3 through 5 the sample includes all respondents aged 15 and over who were not working at the time of the survey but were willing to work at any point in the four weeks up to the survey. Individual controls include gender, polynomials of degree 2 of age and education, ethnicity, household size, marital status, household income and (for columns 3 to 5) months spent looking for a job. Standard errors clustered at the district level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Effect of temperature on methods used to find work

	(1) Employment agency	(2) Showing at firms	(3) Placing ads	(4) Answering ads	(5) Internet search	(6) Relatives or friends	(7) Materials to start business	(8) Day labor	(9) Financing to start business	(10) Other
Average temperature (°C)	0.011***	0.008*	0.003	-0.002	-0.001	0.010**	0.003**	-0.001	-0.000	0.001**
	(0.003)	(0.005)	(0.002)	(0.003)	(0.003)	(0.004)	(0.001)	(0.002)	(0.001)	(0.000)
Observations	12,912	12,912	12,912	12,912	12,912	12,912	12,912	12,912	12,912	12,912
R^2	0.083	0.093	0.073	0.148	0.164	0.173	0.020	0.081	0.024	0.021
Dependent variable mean	0.133	0.383	0.142	0.267	0.164	0.554	0.038	0.113	0.022	0.007
Adjusted p-value	0.007	0.469	0.734	0.985	0.985	0.212	0.224	0.985	0.985	0.300
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Dependent variables are indicators for having used the corresponding method to look for work in the 4 weeks to the survey date. Employment agency refers to having registered at an employment agency. Showing at firms implies enquiring for work at workplaces, farms, factories, or other possible employers. Placing ads involves the placement of advertisements in public areas. Answering ads means to answer help wanted ads. Internet search means searching through job advertisements on the internet. Relatives or friends means seeking assistance for work from relatives or friends. Materials to start business means looking for land, building, equipment or applied for permit to start own business or farming. Day labor means that the jobseeker waited at the side of the road to be hired. Financing to start business means that the jobseeker sought financial assistance to start a new business. The sample includes all respondents aged 15 and over who were not working at the time of the survey but were willing to work at any point in the four weeks up to the survey. Individual controls include gender, polynomials of degree 2 of age and education, ethnicity, household size, marital status, household income and months spent looking for a job. Adjusted p-value corresponds to p-values obtained using the Westfall-Young step-down procedure to control for the familywise error rate. Standard errors clustered at the district level in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Effect of temperature on unemployment and search behavior - Effects by gender of respondent

	(1) Labor force participation	(2) Unemployed	(3) Search methods	(4) Money spent to look for work	(5) Likely to find a job within 2 years
Temperature × Female	-0.002	0.000	0.035***	0.011	-0.004
	(0.002)	(0.002)	(0.011)	(0.024)	(0.002)
Temperature × Male	0.002	0.002	0.029*	0.034	-0.003
	(0.002)	(0.002)	(0.016)	(0.023)	(0.003)
Observations	94,714	48,218	12,910	10,545	10,277
R^2	0.295	0.182	0.253	0.180	0.159
Same	0.0433	0.299	0.650	0.428	0.890
Individual controls	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes
Year-by-month FEs	Yes	Yes	Yes	Yes	Yes

Note: Dependent variables are indicators for participation in the labor force and unemployment (columns 1 and 2), the number of methods used to look for a job in the four weeks to the survey (column 3), the amount of money spent on transportation in the seven days to the survey to look for work (column 4, measured in South Africa Rand of 2008), and the stated probability of finding a job within two years (column 5). The variables of interest are the average temperature (in º C) in the district in the 30 days to the survey date (7 days in the case of column 4) and its interaction with indicators that take the value of one if the respondent is female (row 1) and male (row 2). The row "Same" resports the p-value of the null hypothesis that the effect is the same for both groups. In column 1 the sample corresponds to all respondents aged 15 and over. In column 2 the sample includes all respondents aged 15 and over in the labor force. In columns 3 through 5 the sample includes all respondents aged 15 and over who were not working at the time of the survey but were willing to work at any point in the four weeks up to the survey. Individual controls include polynomials of degree 2 of age and education, ethnicity, household size, marital status, household income and (for columns 3 to 5) months spent looking for a job. Standard errors clustered at the district level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect of temperature on unemployment and search behavior - Effects by ethnicity of respondent

	(1) Labor force participation	(2) Unemployed	(3) Search methods	(4) Money spent to look for work	(5) Likely to find a job within 2 years
Temperature × African	-0.001	0.003	0.025**	0.015	-0.004*
	(0.002)	(0.002)	(0.012)	(0.020)	(0.002)
Temperature × Other	-0.003	-0.000	0.054**	0.077	-0.005**
	(0.003)	(0.002)	(0.021)	(0.051)	(0.002)
Observations	94,712	48,215	12,901	10,519	10,266
R^2	0.294	0.181	0.252	0.162	0.159
Same	0.583	0.377	0.247	0.232	0.579
Individual controls	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes
Year-by-month FEs	Yes	Yes	Yes	Yes	Yes

Note: Dependent variables are indicators for participation in the labor force and unemployment (columns 1 and 2), the number of methods used to look for a job in the four weeks to the survey (column 3), the amount of money spent on transportation in the seven days to the survey to look for work (column 4, measured in South Africa Rand of 2008), and the stated probability of finding a job within two years (column 5). The variables of interest are the average temperature (in º C) in the district in the 30 days to the survey date (7 days in the case of column 4) and its interaction with indicators that take the value of one if the respondent is African or black (row 1) or from other ethnic group (White, Coloured or Asian, row 2). The row "Same" resports the p-value of the null hypothesis that the effect is the same for both groups. In column 1 the sample corresponds to all respondents aged 15 and over. In column 2 the sample includes all respondents aged 15 and over in the labor force. In columns 3 through 5 the sample includes all respondents aged 15 and over who were not working at the time of the survey but were willing to work at any point in the four weeks up to the survey. Individual controls include polynomials of degree 2 of age and education, ethnicity, household size, marital status, household income and (for columns 3 to 5) months spent looking for a job. Standard errors clustered at the district level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Effect of temperature on unemployment and search behavior - Effects by level of education of respondent

	(1) Labor force participation	(2) Unemployed	(3) Search methods	(4) Money spent to look for work	(5) Likely to find a job within 2 years
Temperature × Low education	-0.002	0.002	0.043***	0.018	-0.004
	(0.002)	(0.003)	(0.016)	(0.030)	(0.003)
Temperature × High education	0.001	0.001	0.030**	0.021	-0.003*
	(0.002)	(0.002)	(0.012)	(0.022)	(0.002)
Observations	94,714	48,217	12,910	10,539	10,274
R^2	0.301	0.176	0.257	0.180	0.163
Same	0.276	0.607	0.412	0.925	0.720
Individual controls	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes
Year-by-month FEs	Yes	Yes	Yes	Yes	Yes

Note: Dependent variables are indicators for participation in the labor force and unemployment (columns 1 and 2), the number of methods used to look for a job in the four weeks to the survey (column 3), the amount of money spent on transportation in the seven days to the survey to look for work (column 4, measured in South Africa Rand of 2008), and the stated probability of finding a job within two years (column 5). The variables of interest are the average temperature (in º C) in the district in the 30 days to the survey date (7 days in the case of column 4) and its interaction with indicators that take the value of one if the respondent has not completed basic education (Grades 0 through 9, row 1) or they did complete it (row 2). The row "Same" resports the p-value of the null hypothesis that the effect is the same for both groups. In column 1 the sample corresponds to all respondents aged 15 and over. In column 2 the sample includes all respondents aged 15 and over in the labor force. In columns 3 through 5 the sample includes all respondents aged 15 and over who were not working at the time of the survey but were willing to work at any point in the four weeks up to the survey. Individual controls include polynomials of degree 2 of age and education, ethnicity, household size, marital status, household income and (for columns 3 to 5) months spent looking for a job. Standard errors clustered at the district level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Appendix A Additional Figures and Tables

Table A1: Relationship between temperature and respondent characteristics

Covariate	Estimate	Standard error	Observations
Male	0.002	0.002	12912
Age	0.054	0.068	12912
African	0.001	0.003	12912
Coloured	-0.001	0.003	12912
Asian/Indian	-0.000	0.000	12912
White	0.000	0.001	12912
Married	-0.002	0.003	12912
Household size	0.031	0.033	12912
Urban area	0.004	0.004	12912
Years of education	0.025	0.018	12912
Household income	-22.455	32.714	12912
Unemployment spell (months)	0.413	0.279	12912

Note: Standard errors clustered at the district level. Each row presents the coefficient of regressing the covariate on the average temperature in the 30 days to the survey date (in degrees Celcius). Male is and indicator that takes the value of one if the respondent is male. African, Coloured, Asian/Indian and White are indicators that take the value of one if the respondent is of the corresponding ethnicity. Married is an indicator that takes the value of one if the respondent is married. Urban area is an indicator that takes the value of one if the respondent lives in an urban location within the municipality. Estimates are based on OLS regressions that include district fixed effects and year, month and month-by-year fixed effects. All estimates The sample is composed of individuals aged 15 or more who do not have a job at the time of the interview but are willing to work.

Table A2: Determinants of survey attrition

	(1) Not found in following wave	(2) Not found in following wave	(3) Not found in following wave	(4) Not found in following wave	(5) Not found in following wave	(6) Not found in following wave
Temperature in the following 2 years	0.023	0.023	0.012	0.022	0.012	0.004
	(0.027)	(0.027)	(0.029)	(0.027)	(0.029)	(0.030)
Number of methods used to find work		0.000			-0.002	-0.002
		(0.004)			(0.004)	(0.004)
Money spent looking for a job			0.000*		0.000*	0.000***
			(0.000)		(0.000)	(0.000)
Likely to find a job within 2 years				0.008		0.006
				(0.015)		(0.019)
Observations	10,072	10,072	8,117	8,139	8,106	6,563
R^2	0.030	0.030	0.036	0.035	0.036	0.042
Dependent variable mean	0.215	0.215	0.216	0.218	0.216	0.220
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FEs	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is an indicator that takes the value of one if an individual surveyed in a round was not interviewed in the following round. Temperature in the following 2 years corresponds to the average temperature during the 2 years after the interview took place in the district where the respondent was surveyed. Unemployed is an indicator that takes the value of one if the individual is not employed but is willing to work at the time of the survey. Number of methods used to find work is a count variable that record the number of methods (among the ones probed) that unemployed individuals have used in the 30 days prior to the survey to find work. Money spent looking for work is the amount of money job seekers used to find work in the seven days prior to the survey. Likely to find a job within 2 years is an indicator that takes the value of one if the individual manifested at the time of the survey that it was likely that they would find a job in the following two years or less. The sample includes all respondents aged 15 and over who appeared in waves 1 through 4 and who were not working at the time of the survey but were willing to work at any point in the four weeks up to the survey. Individual controls include gender, polynomials of degree 2 of age and education, ethnicity, household size, marital status, household income and months spent looking for a job. Standard errors clustered at the district level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Effect of temperature on the probability of migration

	(1) Migrant	(2) Migrant	(3) Migrant
Temperature in the previous month	0.002		
	(0.008)		
Temperature in the previous 6 months		0.005	
		(0.014)	
Temperature in the previous year			0.002
			(0.027)
Observations	7,047	7,047	7,047
R^2	0.181	0.181	0.181
Dependent variable mean	0.0738	0.0738	0.0738
Individual controls	Yes	Yes	Yes
District FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes
Year-by-month FEs	Yes	Yes	Yes

Note: The dependent variable is an indicator that takes the value of one if the individual is in a different district council than in the previous wave. The variables of interest are the average temperature (in º C) in the origin district in the 30 (row 1), 180 (row 2) and 365 (row 3) days to the survey date. The sample includes all respondents aged 15 and over who appeared in a previous wave and who were not working at the time of the survey but were willing to work at any point in the four weeks up to the survey. Individual controls include gender, polynomials of degree 2 of age and education, ethnicity, household size, marital status, household income and months spent looking for a job. Standard errors clustered at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Effect of temperature on the perceived probability of finding a job

	(1) Likely to find a job in 1 month	(2) Likely to find a job in 3 months	(3) Likely to find a job in 6 months	(4) Likely to find a job in 1 year	(5) Likely to find a job in 2 years
Average temperature (°C)	-0.000	-0.003	-0.002	-0.004	-0.014*
	(0.003)	(0.004)	(0.004)	(0.004)	(0.008)
Observations	10,138	6,411	5,918	3,708	1,716
R^2	0.088	0.085	0.099	0.150	0.198
Dependent variable mean	0.246	0.259	0.398	0.551	0.382
Adjusted p-value	0.892	0.863	0.87	0.828	0.334
Individual controls	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes
Year-by-month FEs	Yes	Yes	Yes	Yes	Yes

Note: Dependent variables are indicators that take the value of one if the respondent answered affirmatively. Questions are asked in order, from shorter to longer time frame. Those who answer "Yes" to one question are not asked subsequent questions. The sample includes all respondents aged 15 and over who were not working at the time of the survey but were willing to work at any point in the four weeks up to the survey. Individual controls include gender, polynomials of degree 2 of age and education, ethnicity, household size, marital status, household income and months spent looking for a job. Adjusted p-value corresponds to p-values obtained using the Westfall-Young step-down procedure to control for the familywise error rate. Standard errors clustered at the district level in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$