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Learning by searching: Spatial mismatches and imperfect information in Southern labor markets[☆]

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ABSTRACT

Youth unemployment remains extremely high throughout the developing world, at times coexisting with unmet demand for labour and high job turnover. We examine one possible explanation for this: spatial mismatches between jobs and job-seekers combined with high search costs can lead young job-seekers to have overly optimistic beliefs about their employment prospects. As a result, job-seekers under-search but also hold out for better jobs. Through a field experiment we find that reducing search costs through transport subsidies leads job-seekers to search more intensively and to adjust their beliefs in line with their search experience. When jobs fail to materialize immediately, job-seekers who believed that dropping CVs at prospective employers in the city centre was an effective search strategy become more impatient, they lower their reservation wage and they settle for low-paying jobs closer to home. This does not increase their likelihood of being employed, since nearby jobs are also scarce. These findings underscore both the importance and the complexity of the interaction between search costs and beliefs, and how they can lead to spatial and occupational mistargeting in the job search.

1. Introduction

Unemployment rates for young job-seekers remain staggeringly high across the developing world, with official figures ranging from 21% in Rwanda to 60% in Uganda.[1] Persistent youth unemployment poses significant economic and social challenges to developing economies, compromising lifetime earnings, reducing incentives to invest in education, and potentially leading to increased criminal activity (Fougere et al., 2009). Given the rising demographic pressure throughout the developing world, understanding the constraints to youth employment and designing effective labour market policies to remove them remains a pressing policy issue today.

In an attempt to identify the labour market frictions that could explain these figures, two emerging streams in the literature have focussed on the role of search costs (McKenzie, 2017; Abebe et al., 2018) and on the role of beliefs about jobs (Groh et al., 2015; Abebe et al., 2020).[2] This paper focuses on the potential *interaction* between search costs and beliefs. High search costs often arise from spatial mismatches between jobs that are typically located in the city centre, and job-seekers who live farther away in low-income neighbourhoods. Physical distance can also exacerbate social divides and homophily in social and professional networks, which combined, greatly reduce the accuracy of information available to first-time entrants to the job market and can ultimately lead to distorted beliefs. We design a field experiment to examine how reducing search costs shapes learning through the

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[1] Youth unemployment rates are significantly higher than overall unemployment rates in Sub-Saharan Africa, ranging from Uganda (60%, Bandiera et al. 2020); Angola (54%); Namibia (43%); Nigeria (38%); Cape Verde (32%) to Rwanda (21%)(Source: National Statistical Agencies compiled by tradingeconomics.com). The African Development Bank predicts that youth unemployment rates across the sub-continent will reach 50% on average by 2025 (African Development Bank 2018).

[2] The literature is significantly more advanced in the developed world context (Spinnewijn, 2015; Mueller et al., 2020).

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job search, and how this in turn affects beliefs and explains employment outcomes.

Our experiment takes place in Johannesburg, South Africa, a country where high estimated youth unemployment coexists with strong demand for labour (Banerjee et al., 2008).[3] Like a growing number of cities in the developing world, Johannesburg combines limited transport infrastructure with a spatial mismatch between jobs and low-income job-seekers, which results in very high search costs.[4] Our sample consists of 1082 job-seekers in a large township in the outskirts of Johannesburg, aged between 18 and 32, who have completed at least secondary education, and who are actively searching for jobs.[5]

We begin by documenting a striking optimism bias among job-seekers with respect to entry-level jobs: expected salaries at baseline are on average 1.7 times higher than the actual average salaries reported by employed individuals in the region with similar skills and age profiles. This bias appears to be driven mostly by an overestimation of the probability of getting into entry-level jobs in high-paying occupations, as opposed to inaccurate information about the entry-level wages for each type of job: 75% of job-seekers reported looking for a professional job, even though the actual probability of getting a professional job for an individual with a similar age and skill profile is only 11%.[6] Moreover, respondents are also over-confident: they believe that their own starting salary is likely to be on average twice as large as the salary of job-seekers in their township who have a similar skill profile. In fact, respondents are optimistic across the board since they overestimate the probability of getting any type of job — 62% of them believe that it is likely or very likely that they will find a job within 2 months, despite having been on the job search for an average of 15 months. In this sense, our sample is similar to samples drawn from other labour force surveys in South Africa, which show average search time for jobs of 12 months or longer and high general levels of optimism (ILOSTAT, 2015; StatsSA, 2015).[7] Since search costs for the city centre jobs they aspire to are high, search intensity is low and learning remains slow.

Our field experiment has three key features. First, we release the transport constraint by providing job search subsidies to a subset of randomly selected job-seekers and observe their search activity through the main bus rapid transit (BRT) network connecting the township to the city centre. Within the subsidy group, we randomize whether the recipient can decide to use the subsidy on anything other than transport.[8] Second, we elicit beliefs about a range of aspects relevant to the job search, including the level of skill required for different types of jobs and associated wages, as well as beliefs about the key binding constraints to finding a job such as skills and transport costs. Importantly, we measure beliefs before, and twelve months after, the job search subsidy intervention. Third, we measure several features of the job search including the frequency of travel to the city centre, as well as employment decisions. The structure of the experiment helps us understand how search experience shapes beliefs and how beliefs drive subsequent employment decisions.

We find that providing job search subsidies reduced search costs as participants in the treatment group searched more intensively than those in the control group, by travelling more frequently and by covering a wider geographic area in the job search. This occurs even when the subsidy is unconditional and does not need to be spent on travel, suggesting that the job-seekers genuinely believe that transportation is a constraint. We then find that job-seekers who travel more intensively in search of jobs revise their beliefs in line with their search experience: treated job-seekers update their beliefs about their employment prospects, leading to a decrease in salary expectations (5%) and in reservation wages (8%). They revise downward the probability of getting a high-paying job in the city and they report a significant increase (23%) in their valuation of existing jobs, measured by the expected number of days job-seekers think it would take for them to find another job, if they were to lose the one they had. Finally, in line with their downgraded beliefs, job-seekers were more impatient (a 15% change relative to the control group) and more likely to search in their own township relative to the control group (by a factor of 2). This redirection of search towards the township results in them being 9% percentage points (a 77% change relative to the control at endline) more likely to settle for a lower-paying job in their own township, despite having reported a preference for a job in the city centre at baseline. This effect is driven primarily by the 64% of job-seekers who at baseline held strong beliefs about the importance of travelling to prospective employers and dropping their CVs as an effective job search strategy.[9] Jobs in the township are even scarcer than in the city centre and those in the control group who manage to search unsubsidized in the city centre are positively selected on skill and are more likely to be male so levels of actual employment end up being similar across treatment and control groups twelve months after the start of our intervention. The main difference is that those who settle on a township job are paid less and wages increase much more slowly for jobs in the township, so our (rough and ready) calculation suggests that this switch may come at a very substantial loss of life-time earnings.[10]

[3] An estimated 54% of South Africa's population aged 15–24 reports being unemployed (ILOSTAT, 2015).

[4] Most jobs are located in the central business district (CBD) or in the surrounding industrial belt, but the majority of low-income job-seekers live in townships that are on average 20 kms away. While Johannesburg might be an extreme case, there is growing evidence that poor urban planning and limited transport infrastructure are leading to similar spatial mismatches across large cities in the developing world (Abebe et al., 2018; Franklin, 2017; Abebe et al., 2021). Our findings are therefore likely to become increasingly relevant in several settings characterized by urban sprawl and high transport costs.

[5] This sample is very similar to the sample surveyed in the Labour Market Dynamics Survey for South Africa –LMDSA– (2015) for individuals aged between 18–32 living in the Gauteng province as shown in Table A1 in the Online Appendix.

[6] The official 2015 wave of the LMDSA revealed that individuals in the age group 18–32 holding secondary education in the greater Johannesburg region were employed mostly in services and elementary occupations (45%) or as clerks (16%). Only 11% worked in professional job categories in business or in government.

[7] In existing labour force surveys, about 82% of those unemployed report to have been searching for jobs for over a year and approximately 30% have searched for jobs for over 5 years (StatsSA, 2015). Figure A6 in the Online Appendix shows that respondents to the LMDSA were on average optimistic about improving their financial situation in the following two years. The exact question used in the LMDSA is "Please imagine a six step ladder where the poorest people in South Africa stand on the bottom (the first step) and the richest people in South Africa stand on the highest step (the sixth step). On which step are you today?" and "On which step do you expect to be 2 years from now?". Our measure of ladder changes in the histogram corresponds to the difference between where the respondent expects to be in 2 years and where the respondent was in 2015. Over 60% of respondents expected that their financial situation would improve in the subsequent 2 years. The LMSA sample is similar to ours in terms of gender, education and age group (18–32).

[8] In the end, we find no difference between these treatments as most of the funds are spent on transport. Our analysis therefore pools the two treatments.

[9] This evidence on changes in beliefs is inconsistent with an alternative interpretation in which the switch to searching in the township is driven by financial constraints due to delayed job finding. Moreover, treatment effects do not differ across participants with different levels of initial income and the total number of months in employment is similar between treatment and control groups. Finally, we do not find that at endline those reporting lower monthly income are more impatient. It is therefore unlikely that financial constraints would bind more for the treatment group than for the control group.

[10] We conduct a back of the envelope calculation to estimate the loss in lifetime earnings from having a job in the township relative to having a job in the CBD, based on wage data from a combination of sources (Harambee, the National Income Dynamics and the National Household Travel Survey). These data suggest a 30–40% drop in lifetime earnings from employment in the township.

Our findings reveal that imperfect information about employment prospects and on how to find a job is pervasive and that because information is multi-dimensional, it is hard to correct through increased access to the labour market alone.[11] In environments characterized by high transport costs to areas where the good jobs are located, many job-seekers believe that their best strategy is to apply in person whenever they have a chance. But temporarily reducing transport costs to give them a chance to apply may not improve employment outcomes, while also potentially leading to the wrong lesson being learned. When the external access constraint is lifted, job-seekers search intensively, but given that jobs are scarce and job-seekers may be mistargeting, many of them will find that jobs fail to materialize immediately. The inference from this experience depends on their priors. In particular, if they start by believing that there are enough jobs and that the key strategy to find them is to travel to the city centre and leave CVs with prospective employers, then the failure to find their desired job after searching intensively might lead them to blame their own lack of skills or to grow impatient with the search process. These are, in fact, the patterns we observe in the data. This implies that policies to support job-seekers in low-income settings characterized by significant spatial asymmetries of information might need to include de-biasing interventions alongside investments to increase access to the labour market, so as to optimally guide job-seekers in the job search and mitigate mistargeting (Altmann et al., 2018).

Our findings sit at the intersection of several literatures. First, they relate to a nascent literature that emphasizes systematic mismatches between the job quality that job-seekers expect and what is available in the labour markets they are searching in (Groh et al., 2015; Blattman et al., 2016; Beam, 2016; Abebe et al., 2018; Mueller et al., 2020). We add to this literature by showing that job-seekers learn through the job search, but that this learning does not necessarily lead them to better outcomes.[12] Note that in our setting, our intervention does not directly change beliefs. Beliefs change due to greater exposure and to learning through the job search.

The second is a literature that uses experimental methods to rigorously evaluate the impact of interventions aimed at reducing labour market search costs on employment outcomes in developing countries (Franklin, 2017; Abebe et al., 2018, 2021; and Abebe et al., 2020, for Ethiopia and Bandiera et al., 2021 for Uganda).[13] In line with Abebe et al. (2018), we find that transport subsidies do not always improve employment prospects in the long-run. Moreover, we provide a potential explanation for these results: distorted priors about employment prospects can lead job-seekers to mistarget their job search and misinterpret the information obtained through the job search process.

Third, we add to a literature on how the distorted beliefs of job-seekers can affect the optimal design of active labour market policies (Spinnewijn, 2015; McKenzie, 2017; Bandiera et al., 2021). Recent survey data, mostly from a developed world context, has identified an optimism bias in job-seekers' beliefs (Spinnewijn, 2015; Conlon et al., 2018; Arni and Schiprowski, 2019; Mueller et al., 2020). We add to this evidence and argue that this makes it more difficult for the job-seekers to learn from their job search experience, leading to suboptimal outcomes.

Finally, we contribute to a literature highlighting the importance of transport infrastructure and urban planning for growth (Duranton and Turner, 2012; Redding and Turner, 2015). We provide descriptive evidence on how physical and social distance from jobs can shape professional networks and access to information during the job search, and consequently, spatial patterns of employment. Moreover, we add to this literature by highlighting how transport costs can flatten the spatial wage gradient for entry-level jobs for large cities in the developing world. This may result in young job-seekers settling for jobs with lower pay gradients, thus compromising their lifetime earnings and perpetuating inequality and cycles of poverty.

2. Empirical setting

By 2050, a billion people are projected to be living in Sub-Saharan Africa's largest cities (OECD 2019). One of the biggest challenges facing the sub-continent is that most of this growth is already happening through urban sprawl due to the lack of adequate urban and landscaping policies.[14] Urban sprawl is likely to have profound effects on the types of jobs that different segments of the urban population can access. The spatial dispersion that characterizes most large African cities often places low-income groups in urban slums and in townships outside the urban core. In fact, the population living in the outskirts of major economic centres in Africa is expected to triple in the next three decades (CSIS 2019).

We study the labour market of Gauteng in South Africa, a region characterized by the urban core of Johannesburg and Pretoria, and the surrounding townships where the majority of low-income groups live. Most townships are at least 20 km away from the central business district of Johannesburg, where the high-paying jobs are located.

We follow a randomly selected sample of 1082 job-seekers in the Soweto township, outside of Johannesburg, who were listed as actively seeking a job in the South African National Youth Development Agency (NYDA) and in the Department of Labor's Employment Services of South Africa (ESSA) databases.[15] 98.5% of the Soweto population is black African and employment rates are estimated to be low (35%). Average income is ZAR 2400 (185 USD),[16] which represents 70% of the median minimum wage in the broader Johannesburg region.[17]

Table 1 shows the demographic and household characteristics of our sample and Table 2 shows their employment and job search history.

Our sample of job-seekers is aged between 18 to 32, the vast majority of which (83%) have completed secondary education. The

[11] In the economics literature the difficulty of Bayesian observational learning about multiple dimensions has been emphasized, for example, by Piketty (1995) and documented in social psychology as the fundamental attribution error (Ross, 1977).

[12] While other papers have examined how job-seekers learn about the wage offer distribution through experience (Burdett and Mortensen, 1998; Conlon et al., 2018), they were conducted with experienced job-seekers in a developed economy context, for whom baseline informational frictions are likely to be significantly lower. Both studies conclude that despite significant heterogeneity in beliefs about the wage distribution, learning occurs relatively quickly with workers fast converging to the true wages. Our findings provide new evidence on how this process may be different in labour markets characterized by structural informational frictions.

[13] See also Phillips (2014) for examples from the United States. Discussions about spatial mismatches leading to unemployment go back to Holzer (1991); Wasmer and Zenou (2002); and Selod and Zenou (2006).

[14] In the United States, it is estimated that urban sprawl costs the economy 1 trillion per year, or 5.4 percent of GDP (Victoria Transport Institute 2015). While there is no similar statistic for Sub-Saharan Africa, by 2050, urban land cover in Africa is expected to be four times higher than it was in 2000 (Angel et al., 2005). Recent evidence already suggests that the average African city is 20% more fragmented and dispersed than the average city in Asia (Lall et al., 2017).

[15] The South African National Youth Development Agency (NYDA) is an agency tasked with supporting young job-seekers gain access to the labour market through career advice and the provision of information on job vacancies. We use this sampling frame to identify individuals who are actively searching for jobs. The fact that about 46% of our sample reported not using the labour centres at the NYDA or any other government agency to seek support during the job search in the year prior to our baseline survey, allays our concerns about the external validity of our findings given that job-seekers enrol in the database but do not seem to effectively rely much on the services of this agency during the job search.

[16] All values are converted into USD at 2015 prices.

[17] ZAR 2400 corresponds to 70% of the median minimum wage in the retail sector in the Johannesburg area (StatsSA, 2015).

Table 1
Job seeker household characteristics at baseline.
Source: Survey data.

	Mean	Std	Min	Max	N
Age of job seeker	25	3	18	32	1082
Completed secondary education	0.83	na	0	1	1082
Attended or Completed tertiary education	0.17	na	0	1	1082
Number of household members	4	2	1	15	1082
Share of employed Hh members (18–65)	0.27	na	0	1.00	1082
Total (individual) income, previous month (ZAR)	622	1241	0	7300	1077

remaining 17% have attended or completed tertiary education. Among household members aged between 18 and 65, only one person out of 4 is likely to be employed. Total individual income is on average low at approximately 50 USD (622 ZAR), representing, for the most part, earnings from casual jobs.[18]

In 2014, at baseline, 57% of the sample had worked in at least one job in the previous 3 years, and the average length of time job-seekers had been searching for a job was 15 months.[19] Most job-seekers appear to be actively searching for a job, though not intensively as search costs are high with reported monthly transport costs representing approximately 31% of monthly income. The average job seeker submitted 12 applications in the 5 months prior to our survey and only about half of the sample attended at least one job interview in the previous 3 years.

3. Main findings: Imperfect information about jobs

3.1. Beliefs about wages and job prospects

We begin by documenting that job-seekers hold imperfect information about key parameters of the job search and about potential employment opportunities. First, the majority of job-seekers (almost half) are looking for a professional job in business or in the financial sector, followed closely by government jobs (see Figure A1 in the Online Appendix). The official Labor Market Dynamic Survey in South Africa (LMDSA 2015), revealed that the probability of accessing a government or a professional job is closer to 11% for individuals with the same age, educational profile and geographic location as those in our sample.

Job-seekers are therefore over-optimistic about their own entry-level wages. When we compare reported expected salaries in our survey to the median actual salary of individuals with the same age, race and education, in the Johannesburg area captured in the LMDSA (2015), we find that over 90% of job-seekers hold positively biased beliefs about their future wages.[20] The median market wage is approximately 3000 ZAR (230 USD), and job-seekers at the mid-point of the distribution expect to receive almost twice this amount (see Fig. 1).[21]

We then try to unpack the main source of this bias. This sizeable wedge may be driven by: (i) an overestimate of the within or cross-occupation wage distribution, (ii) an overestimate of the probability of accessing a high-paying job category, or some combination of the two. We compute median occupation-based wedges between expected monthly earnings (from our survey) and actual monthly earnings (from the LMDSA survey), for the main job categories that job-seekers report searching for.[22] Fig. 2 shows median expected take-home salaries reported by our sample relative to the actual median take-home salaries for individuals in a similar age group and with a similar level of education in the Johannesburg area (LMDSA 2015).[23]

In sample median expected earnings for jobs that can typically be found in the township – manufacturing, sales and construction – are close to the actual median monthly earnings reported in the LMDSA, but for jobs that are available in the city centre – government and

Fig. 1. Salary bias at baseline (expected vs. actual median wage). Notes: Wedge between expected own salary and the actual median salary of employees with a similar educational and age profile, pooled across the job categories that the job-seekers report targeting in the job search. The vertical reference line represents the median salary reported in the LMDSA (2015) for individuals with secondary education, aged between 18 and 32 in the Johannesburg region: 3000 ZAR (230 USD).
Source: Survey data and LMDSA 2015.

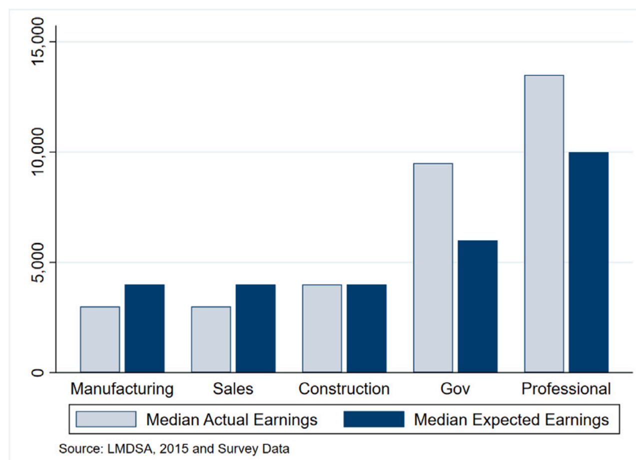


Fig. 2. Expected vs. actual median wage by job category. Notes: Actual median take-home salaries for employees aged between 18–32 and with a secondary education degree, in each job category.
Source: Expected Earnings from Survey Data and Actual Earnings from LMDSA (2015).

[18] Only 4% of job-seekers in our sample are receiving unemployment insurance, which represents 33% of their average monthly income reported at baseline.

[19] This is very similar to the average 12 months search period that young job-seekers have reported in other surveys in South Africa (ILOSTAT, 2015).

[20] The exact question asked in our survey to obtain these figures was "How much do you expect to earn as take-home pay in your next job given your level of skill, work experience and education?". These questions were not incentivized. Participants received only air credit to thank them for participating in the survey. The LMDSA also asks about actual take-home pay.

[21] While these figures are already striking, they might represent a lower bound of the true wedge if those in actual employment, and therefore in the official survey data, are positively selected relative to our sample of job-seekers.

[22] The full distribution of median salaries (take-home pay) from the LMDSA (2015) is reported in Figure A2 in the Online Appendix, for all job categories, not just the jobs that our respondents report to be targeting.

[23] Note that our sample is very similar in basic demographics to the sample in the official LMDSA, as shown in Table A1 of the Online Appendix.

Table 2
Job seeker employment and job search history.
Source: Survey data.

	Mean	Std	Min	Max	N
Worked between 2011 and 2014	0.57	na	0	1	1082
If worked, number of jobs	1.46	0.80	1	10	679
If worked, average past wages (ZAR)	2624	1067	0	4000	676
If worked, avg length of past jobs (months)	16	14	1	53	617
Nbr of applications in the last 5 months (*win*)	12.69	19.18	0	100	1082
Nbr of months looking for a job	15.35	16.60	0	168	1082
Had job interview in the last 36 months	0.51	0.50	0	1	1081
Avg. monthly job search transport expenses	193	177	0	1000	1082
Avg. monthly job search related expenses (non-transport)	193	382	0	2675	1082

Notes: *Win* indicates that the data were winsorized at 95%.

business – job-seekers, in fact, underestimate entry wages. Those with professional or government jobs can earn monthly wages that are up to four times higher than the median wage of the distribution, which is 3000 ZAR (230 USD in 2015 prices).

Importantly, for the 57% of our sample that reports having had at least one job in the three years prior to our baseline survey, the median past wage reported was also 3000 ZAR,[24] which is exactly the figure we observe as the median salary in LMDSA that same year. This suggests that the bias is unlikely to emerge from job-seekers never having had a job and therefore having very limited information on market wages for their skill level.

Given that job-seekers appear to hold close to reasonable beliefs about the wage distribution, we then calculate the implicit probability that each job seeker attributes to getting access to a high-paying job. We follow this implicit derivation of expectations given common challenges associated with eliciting accurate probabilities directly from respondents. We start with equation $E(w) = P * W_H + (1 - P) * W_L$, where $E(w)$ represents the reported expected salary, P the probability of accessing a high-paying occupation, W_H the average wage offer in a high-paying occupation (government or professional) and W_L the average wage offer in low-paying occupations (sales, manufacturing and construction). We use expected figures for W_H and W_L since job-seekers get wages approximately right.[25] We solve for probability P and compare this implicit probability of getting a high-paying job to the actual probability observed in the official LMDSA data.

Fig. 3 reports the cumulative probability distribution for P, for those reporting to target professional and government jobs. The actual probability of accessing a professional job is closer to 11% (StatsSA, 2015).

The majority of job-seekers are over-optimistic about the probability that they will get a job in government or a professional job. Less than 10% of job-seekers hold accurate beliefs about the actual probability of getting a high-paying job, while over 50% believe this probability to be four times higher than it actually is.

This figure confirms that the main source of bias in employment prospects is the expected probability of getting a high-paying job in the city centre. Such biased beliefs might persist because it is easier to learn about prevailing wages than it is to learn about the specific probability that one can get into a high-paying occupation in the city business district (CBD). In fact, job-seekers who were previously employed and who may therefore have a more accurate idea of the actual wages for accessible jobs, are also excessively optimistic about their ability to receive a job offer in a higher paying occupation in the near future.[26]

Job-seekers are very optimistic overall as 89% of the sample believes that they will find a job within a year and 62% of them expect to find a job within 2 months, despite having been searching for a job for the past 15 months.[27] Consistent with distorted beliefs about the probability of accessing a high-paying job, job-seekers are overconfident about their own job prospects (Benoît et al., 2015; Moore and Healey, 2008). They expect to earn higher salaries relative to other job-seekers in their township with similar levels of education, as shown in Fig. 4.

Approximately 12% of the sample reports having turned down a job in the previous 3 months, 63% of which were in retail. The main reasons for turning down jobs are low pay (40%) and distance to a job (25%).[28]

3.2. Beliefs about access to jobs

Most job-seekers in our sample (91%) believe that the main place to find jobs that match their skills and interests is outside their Soweto township. Only 21% would prefer to work in the township if they were able to find a job, mostly because travel costs would be lower. The majority of job-seekers in our sample (64%) report that dropping CVs at prospective employers is one of their two top strategies for seeking employment.[29] Out of these, 64% of respondents believe that this strategy is likely or very likely to result in an interview.[30] Consistent with these beliefs, close to 60% of the sample identifies transport as the first or second main obstacle to finding employment.[31] Specifically,

[24] Note that the median wage is slightly higher than the average wage reported in Table 2 due to negative skewness in the data.

[25] Using the expected wages of high-wage and low-wage occupations yields even higher implicit probabilities.

[26] Figure A3 in the Online Appendix shows that wage experience is not correlated with biased beliefs about future salaries at baseline, further suggesting that the source of bias is likely to lie on expectations about accessing high-paying jobs as opposed to the lack of information on actual market wages for their skill level. This graph only includes job seekers who reported having had a job in the past.

[27] Data from the LMDSA (2015) also reveals significant optimism with regards to their financial situation for a sample of respondents that are similar in age, gender, location and education to our sample. See Figure A6.

[28] See Figure A4 in the Online Appendix.

[29] Respondents could select an answer from a list of 10 options including: submitting a CV to job sites online; emailing their CVs; asking friends and family for information; joining placement agencies; signing up with labour brokers; applying for internships; using facilities at government labour centres (e.g. NYDA); looking at newspapers and an "other" option that respondents would have to specify. Only 4% of respondents selected the "other" option.

[30] Note that respondents may feel that while travelling to the city centre and dropping their CV is an effective strategy, high transport costs prevent them from conducting the optimal number of trips to succeed in finding a job. As a result, it is possible that in their response to our question about the probability of finding a job with this strategy they are downgrading their probability of success given the low frequency of trips they are able to make. In fact, at baseline, respondents report spending less than 5 h travelling to the city centre to drop a CV even though the modal return travel time to the city centre by bus is one hour and 40 minutes.

[31] High transport costs and distance to jobs may then push job-seekers to rely on friends and relatives to provide information about job opportunities. Since spatial inequality is likely to be correlated with social inequality, this severely restricts the quality of information that job-seekers are able to gather through their networks, consisting mainly of individuals residing in the same township with similar levels of education. This kind of homophily can significantly exacerbate errors in beliefs (Kets and Sandroni, 2019). Consistent with the

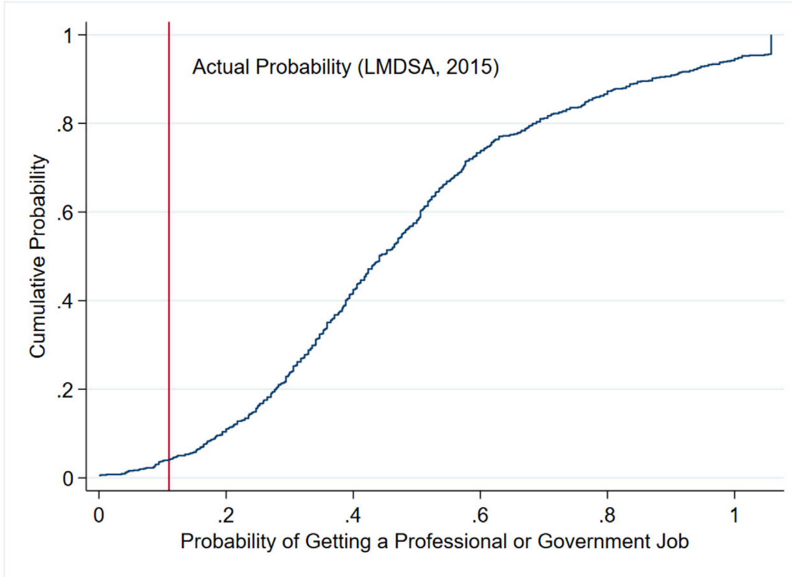


Fig. 3. Cumulative distribution function for the probability of getting a professional or government job.

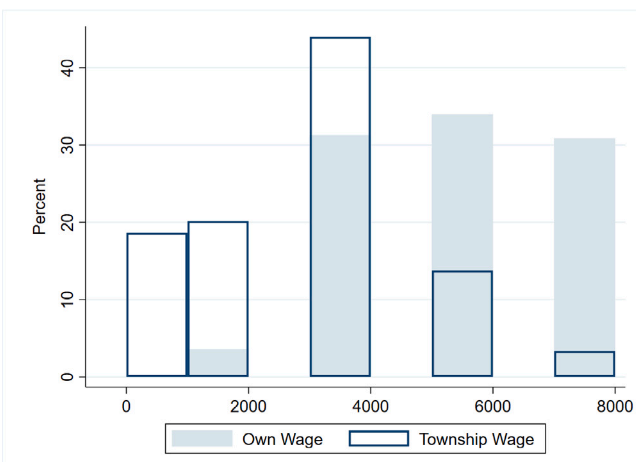


Fig. 4. Distribution of expected own salary and the expected salary for other job-seekers in the township with a similar demographic profile. Notes: Salaries recorded in ZAR. Demographic profile refers to age, educational attainment, and township of residence.
Source: Survey data.

they believe that if they could physically search more intensively in the CBD they would succeed in getting a high-paying job.

Taken together, the evidence suggests that job-seekers under-search for jobs due to high transport costs, while patiently holding on to the belief that they will be able to access high-paying jobs in the future. Moreover, our sample of job-seekers appears to take these beliefs about the job search seriously: when we provide them with an unconditional job search subsidy as described in the next section, by the endline they were using over 70% of it on transport to search for jobs.

4. Experimental evidence: Job search subsidies

Given the evidence on distorted beliefs, we then examine how job-seekers learn from the job search once search costs are reduced. Specifically, we study whether job-seekers adjust their beliefs about jobs in line with their job search experience. To do so, we designed an experiment to encourage a subset of job-seekers to expand their geographic search area and to search more intensively for jobs. We provided 365 individuals (out of 1082) with a transport subsidy that could only be used for transport, and another 352 individuals with a financially equivalent general job search subsidy. The latter subsidy was not restricted to transport but beneficiaries were primed to think about the importance of covering job search costs when they received it. We partnered with the main bus rapid transit system connecting Soweto to Johannesburg's CBD and to the broader industrial belt around Greater Johannesburg to produce smartcards that would allow us to observe how each type of subsidy was spent. While we validate our results in the survey data, using the administrative data also has the advantage of overcoming experimenter demand problems common in studies of job search interventions, where it is clear the experimenter seeks to increase job search.

The transport subsidy and the unconditional job search subsidy were calibrated to represent a similar monetary transfer of ZAR 500 (38 USD) corresponding to 40 return tickets between Soweto and Johannesburg CBD, with an additional ZAR 500 to be used on a secondary bus line that could take job-seekers across greater Johannesburg and Pretoria (approximately 60 km away). The main difference was that the unconditional subsidy could be used for transport or for expenditures in stores, similar to a bank card. The control group received an identical transport smart-card, loaded with a single return trip.[32] Once participants were enrolled in the study, all groups were provided with general

hypothesis that information provided by social networks is a key driver of beliefs and behaviour during the job search, over 60% of our sample considers talking to friends as their primary source of information on the job market (see Figure A5 in the Online Appendix). These findings are in line with previous evidence from the South African Social Attitudes Survey (SASAS, 2014), revealing that a majority (51%) of unemployed people search for jobs by asking friends and relatives for information and support.

[32] Take up of cards was approximately 84%, and it was similar between treatment and control groups. Very few respondents reported having any trouble with using the cards, allaying concerns about differential measurement error across experimental groups. Tables A9 through A11 in the Online Appendix show balance across treatment and control groups and Tables A14 and A15 show balance across individuals who used and did not use the smartcards. Moreover, one concern would be that those in the control group would not value the card as much and lose it or replace it. In our survey, we ask whether the respondent lost the Rea Vaya cards provided. Being in the control group does not predict losing the card (difference between treatment and control = 0.005 (0.0058), p-value = 0.4).

information about how to use the public transport system to access the city centre, with information on schedules, fares, the location of bus stations and routes. Our information pack also included a series of job tips to more effectively search for jobs. This included hard copy information on how to access both government and private sector job vacancy databases, how to write a cover letter and a CV, and how to prepare for a job interview. The informational intervention was very light-touch — we provided no information on actual salaries for different occupations, or on which jobs to target in the job search. As such, our findings should be interpreted as being close to how job-seekers would have naturally searched for jobs and how they would have learned from this experience.

We then examine changes in search activity, beliefs and employment outcomes as a result of the job search subsidies, controlling for baseline characteristics, through the following specification:

$$Y_i = \alpha + \beta * Transport\ Subsidy + X_i + \epsilon_i \qquad (1)$$

where Y_i represents our key outcomes of interest for individual i, β represents the intention-to-treat coefficient of interest and X_i represents a vector of individual level controls including the gender and the age of the job seeker, the length of time the individual had been searching at baseline, whether the job seeker has completed tertiary education and the date in which the individual was assigned to the different treatments during the randomization process. Standard errors are clustered on the date of randomization.[33]

4.1. Changes in search activity

Administrative transport data showed that the treatment groups engaged in approximately 3.5 times more bus trips relative to the control group (see Figures A7 and A8 in the Online Appendix) between our baseline and endline surveys, which were 12 months apart. That this holds even for the unconditional group suggests that job-seekers strongly believe that searching outside of the township is likely to get them a job. In fact, job-seekers who received the unconditional job search allowance spent close to 70% of it on transportation (see Figure A9 in the Online Appendix).[34]

Fig. 5 shows the cumulative total number of trips and the trips taken to the CBD for each experimental group, normalized by group size. It is clear that the treatment groups conducted on average a much higher number of trips to the CBD during our period of analysis.

Table 3 reveals that subsidy recipients travelled farther (in kms) from their home address (column 1) and that they spent more time on average travelling during the 12 months between our baseline and endline surveys (column 2), controlling for baseline characteristics.[35] Note that our subsidy covered approximately 40 round trips between the township and CBD, which most of the sample exhausted within 4–6 months of using the smartcard.[36]

The average trip length of 52 min reported in column 2 is likely to correspond to a one-way trip to the CBD.[37] These findings confirm

Table 3
Job search subsidies and travel.
Source: Survey data.

Dependent variable	Log Tot Dist between home and areas travelled to (km) (1)	Average modal travel time (min) (2)
Treatment	2.607***	16.636***
	(0.157)	(5.113)
Controls		
Age	Y	Y
Gender	Y	Y
Long-term unemployment	Y	Y
Randomization date	Y	Y
Completed tertiary education	Y	Y
Mean Dep Variable Control Group	4.18	52
Std Dev Control Group	2.46	33
Observations	793	542
F-stat	50.19	3.25
R2	0.26	0.02

$Long-term\ Unemployment$ corresponds to a dummy variable that represents 1 if the job seeker has been searching for jobs for a period longer than the median of the distribution of length of search at baseline in our sample. $Randomization\ date$ corresponds to the date in which job-seekers were randomized into the different experimental groups. The sample in column 2 is smaller than in column 1 since it was not always possible to retrieve travel time due to missing-at-random timestamp data. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

that the subsidies enabled job-seekers to gain access to a geographically wider labour market and to engage more frequently in their preferred strategy of dropping CVs at firms located outside of their township, in line with the beliefs and preferences reported at baseline.[38]

4.2. Changes in beliefs about wages and job prospects

Table 4 shows that job-seekers learn through the job search and adjust their beliefs accordingly.[39] Intensifying the job search in the CBD is associated with an 8% reduction in reservation wages and a 5% reduction in expected future wages.[40]

Job-seekers who benefited from the subsidy also revised upwards their beliefs about the value of employment: they believed that if they had a job and lost it, it would take them longer to be able to find another job (34 days longer), as shown in column 3. Subsidy beneficiaries also discount the future more heavily: at endline, respondents in the treatment groups were more likely to require a much larger sum of money in the future to forego a transfer today (column 5).[41] This suggests that exposure to the wider labour market reduced the extent of the distorted beliefs that job-seekers held but it might have also made them too pessimistic about their job prospects and more impatient.[42]

[33] There were 32 randomization days. Treatment and control groups are balanced on several relevant characteristics and attrition was both low at 9.8% (from an original sample of 1200 job-seekers) and balanced, as shown in Sections F, G and I of the Online Appendix.

[34] While it is possible that these expenditure patterns are due to an encouragement effect, this effect should have faded away with time, and is unlikely to be driving behaviour more than 12 months after the end of our experiment.

[35] Table A2 in the Online Appendix shows the estimates without any of the baseline controls.

[36] The samples in columns 1 and 2 are matched to the administrative transport data and are therefore restricted to participants who used their cards during the study. Tables A14 and A15 in the Online Appendix show that there is balance between treatment and control groups in this restricted sample.

[37] Figures A7 and A8 in the Online Appendix show that treated job-seekers travelled more in the main and secondary bus lines. The secondary bus line could get them from the CBD to neighbouring business and industrial areas.

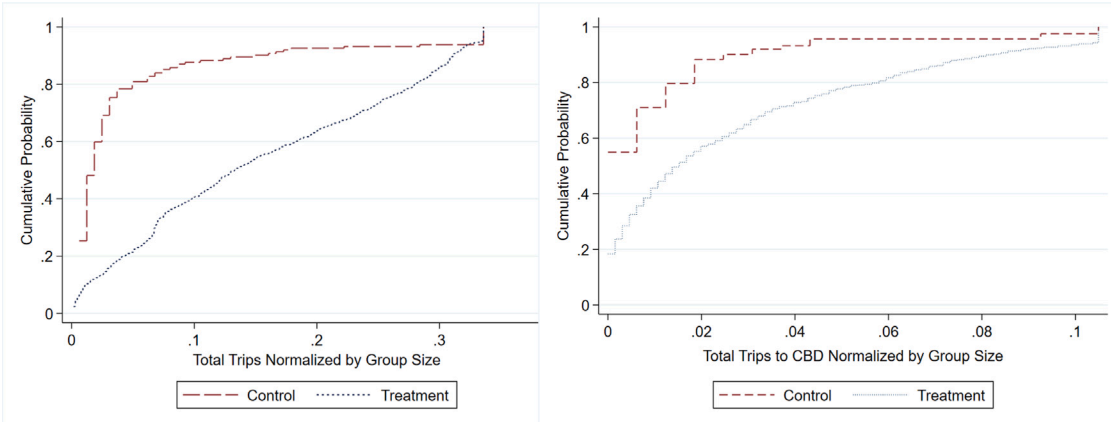
[38] See Figure A10 in the Online Appendix for the geographic spread of the bust stops most frequently used during the experiment by the different experimental groups on the main line connecting Soweto to Johannesburg CBD.

[39] Table A3 in the Online Appendix shows these estimates without the baseline controls and Table A7 shows the results by treatment arm.

[40] This partial adjustment of beliefs is consistent with existing evidence in the literature. Krueger and Mueller (2016) collect rich panel data from unemployed job-seekers in New Jersey and find that reservation wages for the unemployed start high, and do not adjust downward enough, providing suggestive evidence that workers can persistently misjudge their job prospects, or that they have other reasons to hold on to hope.

[41] Measured as how much they would need to receive in 5 weeks' time to forego 300 ZAR (23 USD) today.

[42] This is consistent with theories that emphasize the interaction between being pessimistic about the future and being present-biased (e.g. Banerjee and Mullainathan, 2010). Bartos et al. (2018) shows some experimental evidence suggesting that feeling poor makes people more present-biased.



(a) Panel A (b) Panel B

Fig. 5. Number of trips by treatment status. Panel A reports the cumulative distribution of the total number of trips and Panel B reports the cumulative distribution of the total number of trips to the CBD, both normalized by the experimental group size.
Source: Administrative transport data between baseline and endline.

Table 4
Job search subsidies and changes in beliefs about the job search.
Source: Survey data.

Dependent variable	Log Reservation Wage (1)	Log Expected Wage (2)	Nbr days needed to find another job (3)	Salary Bias (4)	Impatience (5)
Treatment	−0.075**	−0.049**	33.779**	−293.483**	335.363*
	(0.033)	(0.023)	(14.983)	(138.103)	(176.108)
Controls					
Age	Y	Y	Y	Y	Y
Gender	Y	Y	Y	Y	Y
Long-term unemployment	Y	Y	Y	Y	Y
Randomization date	Y	Y	Y	Y	Y
Completed tertiary education	Y	Y	Y	Y	Y
Mean Dep Variable Control Group	8.44	8.75	146	3996	2270
Std Dev Control Group	0.490	0.57	202	3383	2099
Observations	977	1078	1060	1078	1072
F-stat	6.17	4.5	5.78	3.25	1.51
R2	0.01	0.003	0.040	0.002	0.05

$Log\ Reservation\ Wage$ corresponds to the minimum wage respondents would accept for a job; $Log\ Expected\ Wage$ is the expected entry level wage reported by the respondent. $Nbr\ Days\ to\ find\ another\ job$ corresponds to the number of days a respondent expects it would take to find another job if s/he were to lose an existing job. $Salary\ Bias$ consists of the difference between average expected entry-level wage and average actual entry-level wage. $Impatience$ is a measure of how much more the respondent would accept to receive in 5 weeks' time in order to forego a guaranteed transfer of 300 ZAR (23 USD) today. $Long-term\ Unemployment$ corresponds to a dummy variable that represents 1 if the job seeker has been searching for jobs for a period longer than the median of the distribution of length of search in our sample at baseline and 0 otherwise. $Randomization\ date$ corresponds to the date in which job-seekers were randomized into the different experimental groups. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

We then recompute the implicit probability of getting a high-paying job using expected salaries at endline, following the strategy used in Section 3. Fig. 6 compares the implicit probabilities at baseline and at endline. The cumulative distribution of the probability of getting a high-paying job shifts to the left at endline for those in the treatment group, confirming that treated job-seekers revised downwards their expectations about their job prospects.[43]

4.3. Changes in preferences and employment outcomes

In this section we follow a revealed preference approach to learn about changes in participants' preferred job location, given wages and commuting times.

Column 1 of Table 5 reports that job-seekers in the treatment group who had a job between baseline and endline took jobs that were farther from their original preferred place of work, as reported at baseline.[44] Column 2 shows that job-seekers in the treatment group were approximately 9 percentage points more likely to accept jobs in their township, which represents a 77% increase from the control group mean.[45] As a result, they report earning lower monthly salaries (columns 3 and 4).[46] The effect on wages net of reported commuting costs, while negative, is statistically insignificant.

[43] Note that even if these expected probabilities are measured with error, the difference between them at baseline and at endline is still informative.

[44] The corresponding estimates without controls are in Table A4 and the estimates by treatment arm are in Table A8, both in the Online Appendix. Note that the results are similar when we restrict all columns to the minimum common sample.

[45] Only one job seeker reported having a job in a township other than Soweto.

[46] This is consistent with existing evidence on how impatient job-seekers tend to settle for jobs with flatter wage profiles (Munasinghe and Sicherman, 2000; DellaVigna and Paserman, 2005).

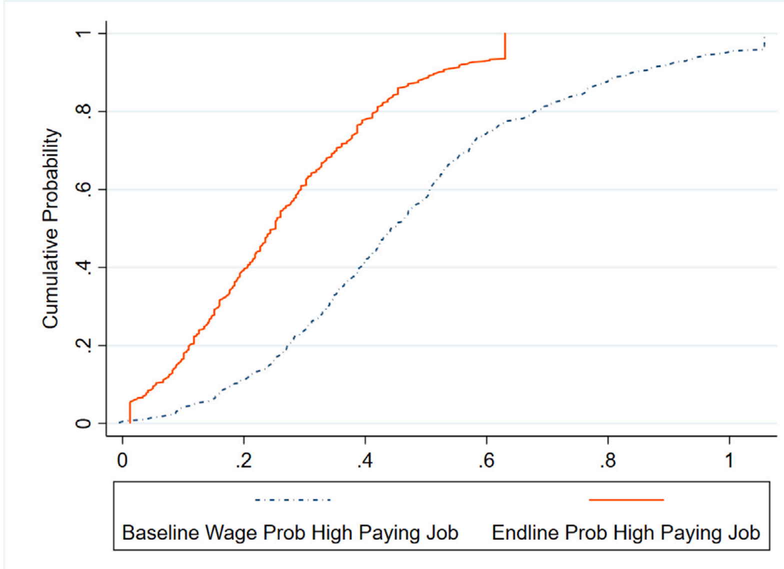


Fig. 6. Cumulative implicit probabilities of getting a professional job in business or in government, before and after the job search intervention, for the treatment group.

Table 5
Job search subsidies: Wages and job location.
Source: Survey data and Administrative transport data.

Dependent variable	Log Distance between Expected-Actual Employment Cond. on having had a Job (1)	Job in Township Conditional on having had a Job (2)	Log Monthly Wage (3)	Monthly Wage Net of Transp. Costs Cond. on Job (4)
Treatment	0.217**	0.075***	−0.201**	−98.924
	(0.106)	(0.027)	(0.090)	(254.625)
Controls				
Age	Y	Y	Y	Y
Gender	Y	Y	Y	Y
Long-term unemployment	Y	Y	Y	Y
Randomization date	Y	Y	Y	Y
Completed tertiary education	Y	Y	Y	Y
Mean Dep Variable Control Group	2.15	0.12	3631	2007
Std Dev Control Group	1.38	0.31	1589	1546
Observations	610	610	360	352
F-stat	1.02	3.36	3.48	4.22
R2	0.01	0.02	0.05	0.05

All columns restrict the analysis to job-seekers who report having had a job between baseline and endline. *Log Distance Between Expected and Actual Employment* is a continuous variable capturing the distance between where the respondent expected to find a job (at baseline) and where s/he effectively found a job. *Job in Township* is a dummy variable indicating whether the job seeker had a job in Soweto between baseline and endline. *Monthly Wage* is reported monthly wage, conditional on having had a job and *Monthly Wage Net of Transport Costs* represents monthly wages net of transport costs as reported by the respondents. 16% of respondents reported having received a transport stipend from their employer, in which case monthly income will be the same as net income. *Long − term Unemployment* corresponds to a dummy variable that represents 1 if the job seeker has been searching for jobs for a period longer than the median of the distribution of length of search at baseline in our sample, and 0 otherwise. *Randomization date* corresponds to the date in which job-seekers were randomized into the different experimental groups. Sample sizes in columns (1) and (2) are smaller as they correspond to the sample we observe in the smartcards, further restricted to those who found a job between baseline and endline. Sample sizes are smaller in columns (3) and (4) as they correspond to those who report having a job at endline. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Finally, we examine whether the increase in job search activity and changes in beliefs affected the extensive margin of employment. Table 6 shows that the treatment group is not more likely to be employed at endline or to have had a job between baseline and endline relative to the control group.[47] One possibility is that visits to the city centre crowded out more efficient job search strategies for the treatment group, resulting in similar levels of employment to those reported by the control group. Our evidence is, however, inconsistent with this hypothesis. We find that job-seekers in the treatment group were just as likely to engage in all types of job search activity relative to the control group, including online submissions of CVs, unsolicited applications

[47] We find no significant differences on the type of employment as the treatment group is not more likely to get a full-time job, to have a permanent contract or to have a professional job. This lack of impact of the job search subsidies on the extensive margin of employment is in line with the long-term findings from Abebe et al. (2018).

Table 6
Job search subsidies and employment outcomes.
Source: Survey data.

Dependent variable	Number of Jobs since Baseline (IHS)		Is currently employed	
	(1)	(2)	(3)	(4)
Treatment	−0.008	0.006	0.01	0.019
	(0.032)	(0.025)	(0.029)	(0.040)
Controls				
Age	N	Y	N	Y
Gender	N	Y	N	Y
Long-term unemployment	N	Y	N	Y
Randomization date	N	Y	N	Y
Completed tertiary education	N	Y	N	Y
Mean Dep Variable Control Group	0.71	0.71	0.74	0.74
Std Dev Control Group	0.52	0.52	0.54	0.44
Observations	1082	1082	1082	1082
F-stat	0.05	9.18	0.07	4.42
R2	0.00	0.03	0.00	0.02

Number of Jobs since Baseline corresponds to the number of jobs the respondent reports to have had since the baseline, including self-employment. This variable is transformed using an inverse hyperbolic sine function. *Employed* is an indicator that corresponds to 1 if the respondent is employed at the time of the endline, 12 months following the baseline, and 0 otherwise. *Long − term Unemployment* corresponds to a dummy variable that represents 1 if the job seeker has been searching for jobs for a period longer than the median of the distribution of length of search at baseline in our sample and 0 otherwise. *Randomization date* corresponds to the date in which job-seekers were randomized into the different experimental groups. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

to vacancies, and requests for referrals from their networks, among others.[48]

An alternative explanation is that there is selection in travel to the CBD in the unsubsidized control group. Figure A15 in the Online Appendix shows that, in fact, those in the control group who travelled the most to the CBD were more likely to be male, to be more active in the job search at baseline and they were more likely to have some tertiary education. As a result, the transport subsidy might have enabled comparatively less search active and less educated job-seekers from the treatment group reach the CBD to search for jobs while leading the slightly more skilled job-seekers to overreact to the low arrival rate of jobs.[49]

Together, this evidence is inconsistent with an alternative interpretation in which changes in search patterns would be driven by delayed job finding: this might imply that those in the treatment group would have searched more in the township due to financial constraints, not necessarily due to changes in beliefs. We find, however, no differential impact of the search subsidies on employment location decisions based on initial income at baseline. Moreover, the average number of months in employment between baseline and endline is similar between treatment and control groups. On the other hand we find substantive evidence of changes in beliefs for those who held stronger priors about job search strategies, which underscores the importance of beliefs in driving this shift.[50]

5. Mechanism

5.1. Learning from experience

At baseline, the majority of job-seekers in our sample (64%) believed that the main reason they had not found a job was because they could not afford to spend enough time in the CBD searching for one. Consistent with this belief, once this constraint was exogenously removed through the job search subsidy, subsidized job-seekers searched more frequently in the CBD, which led them to significantly adjust their beliefs about their job prospects.

Any changes in beliefs will depend on job-seekers' priors. We already noted that job-seekers are on average over-optimistic about their job prospects, and, in particular, that they over-estimate the likelihood of finding professional jobs in the CBD, which are the jobs that they want. Now consider someone who firmly believes that there are enough of these desirable jobs and that physically going to these firms and dropping off their CVs is the only way to get them. For these job-seekers, the fact that they are not successful is likely to suggest that particular skills that they do not have are more important for getting these jobs than they had previously estimated or that jobs are indeed quite scarce. By contrast, those who suspected that jobs were generally hard to find and that dropping CVs would not be an efficient strategy, would update less about the importance of skills and the type of jobs they can access. As a result, the first group, all else equal, would be more likely to conclude that they lack the skills to get their preferred jobs in the city centre or that the arrival rate of jobs is low and therefore become more pessimistic about their own prospects and more impatient in the job search. Since township jobs are perceived to be less demanding of skills (there are very few government or business jobs in Soweto), and easier to search for, those who came to believe through the search process that their skills would not get them the jobs they wanted or that the search process was long and uncertain, should start to search more in the townships and settle for jobs there.

We first confirm that job-seekers who mention dropping CVs as their preferred or second preferred strategy are similar in observables to the other job-seekers in our sample who do not list travelling to drop CVs as a preferred strategy during the job search (see Table A6 in the Online Appendix).

We then expand our Eq. (1) to include an interaction term between receiving the transport subsidies and baseline beliefs about the importance of travelling to the CBD to drop a CV, to examine whether this interaction helps explain both the learning and the employment outcomes observed.[51] Table 7 shows that for the most part, job-seekers with stronger beliefs at baseline about the importance of travelling to potential employers are also the ones who revise downwards their expectations the most once this experience does not translate into higher employment.

These findings are consistent with the very simple theory we suggest where job-seekers have in mind a world in which getting a job depends on multiple factors including physically travelling to drop off a CV

[48] Table A5 in the Online Appendix shows that job-seekers in the treatment group applied to jobs and converted applications into interviews and interviews into jobs at a similar rate as the control group (with a conversion rate of applications to interviews of approximately 17%). Applications can be made online, in-person or through employment apps on a smartphone so it is possible that the intervention may not have changed the total number of applications submitted. Figures A11 through A13 in the Online Appendix further confirm that job-seekers in the treatment group were no less active in searching for jobs online, despite spending more time travelling, since the subsidy increased both transport and non-transport job search activity. It also shows that job seekers in the treatment group were not necessarily more likely to apply to non-advertised vacancies when compared to the control group. The key difference may have been that those in the treatment group were often applying in person.

[49] Table A5 suggests that the "quality" of the search is unlikely to have differed between treatment and control groups as conversion rates of applications into interviews are, on average, similar.

[50] We find no differential treatment effects across participants with different levels of baseline income, different lengths of unemployment at baseline or different demographic characteristics such as age or gender. This is consistent with our interpretation that changes are mostly driven by beliefs.

[51] We restrict our sample to the searchers who we can identify in the administrative transport data. For comparability, this is the sample considered in A5.

Table 7
Beliefs at baseline, learning and employment outcome.
Source: Survey data.

Dependent variable	Log Reservation Wage (1)	Log Expected Wage (2)	Nbr days needed needed to find another job (3)	Salary Bias (4)	Impatience (5)	Job in township (6)
Treatment ∗ Drop CV	−0.138	−0.244*	−21.364	−1135.824*	308.978	0.140***
	(0.093)	(0.127)	(39.506)	(578.774)	(387.108)	(0.039)
Treatment	0.004	0.136	19.693	560.346	−69.291	0.009
	(0.076)	(0.096)	(26.808)	(392.832)	(253.215)	(0.048)
Drop CV	0.007	0.027	34.011	−334.594	−157.782	−0.032
	(0.077)	(0.121)	(27.896)	(506.018)	(259.692)	(0.030)
Controls						
Age	Y	Y	Y	Y	Y	Y
Gender	Y	Y	Y	Y	Y	Y
Long-term unemployment	Y	Y	Y	Y	Y	Y
Randomization date	Y	Y	Y	Y	Y	Y
Completed tertiary education	Y	Y	Y	Y	Y	Y
Mean Dep Variable Control Group	2441	4243	155	8.783	8.497	0.143
Std Dev Control Group	2290	3383	224	0.623	0.496	0.351
Observations	606	607	595	607	542	610
Adjusted R squared	0.030	0.007	0.002	0.050	0.006	0.030

$Log\ Reservation\ Wage$ corresponds to the minimum wage respondents would accept for a job; $Log\ Expected\ Wage$ is the expected entry level wage reported by the respondent. $Nbr\ Days\ to\ find\ another\ job$ corresponds to the number of days a respondent expects it would take to find another job if s/he were to lose an existing job. $Salary\ Bias$ consists of the difference between average expected entry-level wage and average actual entry-level wage. $Impatience$ is a measure of how much more the respondent would accept to receive in 5 weeks' time in order to forego a guaranteed transfer of 300 ZAR today. $DropCV$ is a dummy variable that equals 1 if the respondent identifies dropping a CV in person as the main primary or secondary strategy they think could get them a job and 0 otherwise. $Long-term\ Unemployment$ corresponds to a dummy variable that represents 1 if the job seeker has been searching for jobs for a period longer than the median of the distribution of length of search in our sample and 0 otherwise. $Randomization\ date$ corresponds to the date in which job-seekers were randomized into the different experimental groups. This sample is restricted to job-seekers who we can track in the administrative data. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

and apply to the jobs that they want. Those with these strong priors adjust their beliefs disproportionately more than those with weaker priors, and they are also more likely to settle for a job in the township suggesting an important interaction between beliefs, the search process and employment outcomes.

We report two additional pieces of evidence that are consistent with this interpretation. While there is no difference in total travel between those who believe strongly in "going to the firm and dropping off CVs" and the rest, we would expect the former to start travelling earlier, as soon as they received a subsidy for the search. Fig. 7 confirms that these job-seekers do travel more in the first few months of activating their cards.[52]

Moreover, also consistent with the fact that those who believe in the importance of dropping CVs at potential employers eventually shifts their focus towards jobs in the township, we see from Fig. 8 that job-seekers in the treatment group who accepted jobs in the township at endline reversed search patterns to search more in the township approximately 5 to 6 months after the start of the intervention.[53]

5.2. Consequences of learning from experience

Our findings suggest that job-seekers in the treatment group learned through their experience in the job search, updating their beliefs, changing their search activity and changing their employment decisions accordingly. We also, however, flag the possibility that the inferences made from the evidence depend on the job-seekers' priors and that there is no reason to assume that the decision that they ultimately would have taken under full information would have been correct. In fact, we already noted that the average earnings per month are lower for those in the treatment group who have a job, and that the probability of being employed is almost exactly the same in treatment and control. This is due to the fact that many of the treated job-seekers become very pessimistic about ever finding a job in the CBD with their skill-set, when in fact the process of finding a job in the CBD might simply be lengthy and uncertain, particularly for those with lower skills. If we look at average earnings net of the average monthly cost of commuting to the city centre of 645 ZAR (as reported in our survey), the same result holds, but it is no longer significant (column 4 of Table 5). Note that the earnings gap we report is probably an underestimate since our job-seekers are young, and while wages are in general higher in the city centre, this is particularly so for older, more experienced, workers. Fig. 9 shows average wages for individuals with secondary education for the different age cohorts (18–32 and 32 onwards), by job location, based on survey and official labour force data.[54]

[52] The four month cut-off used in the graph corresponds to the median point of the distribution of the number of days between when each job seeker activated his/her card and each trip for all travellers.

[53] Figure A17 in the Online Appendix shows that those who searched the most in the CBD also searched the most in the township, based on observed search activity in the transport data. Figure A18 in the Online Appendix confirms these findings with the survey data: those in the treatment group who accepted jobs in the township are also more likely to report in the survey that in the previous 4 months they had been searching in the township. This suggests that the township job results from a shift towards active search in the township.

[54] Data on jobs in Soweto were obtained from a survey conducted by a well-established NGO in South Africa that promotes job preparedness among low-income individuals. The survey was conducted between 2018 and 2020 and covers a sample of 765 unemployed respondents who had completed secondary education, aged between 18 and 32, residing in Soweto. Data on wages in Johannesburg CBD were obtained from the NIDS (South Africa National Income Dynamics) for the period 2014/2015, corresponding to a sample of 221 individuals with a secondary education degree and residing in Gauteng. We confirm these values using data from a different source, the National Household Travel Survey (NHTS), conducted in 2013. In this survey respondents are asked about their place of residence and their place of work. The differences in wage gradients between Soweto and Johannesburg across time is even starker in the NHTS dataset. See Figure A20 in the Online Appendix.

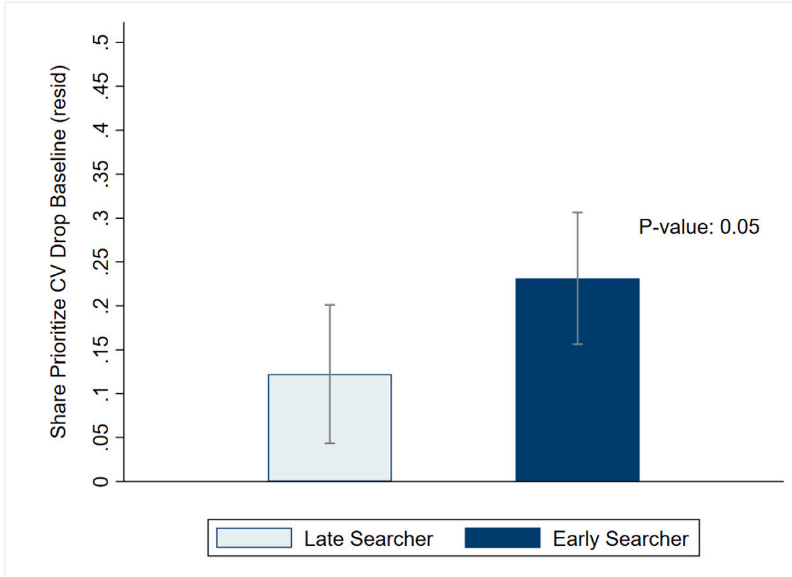


Fig. 7. Share of job-seekers in the Treatment Group prioritizing dropping off a CV in person at baseline and whether the job seeker travelled more in the first four months of activating their transport card. Notes: Share of job-seekers is residualized from the following variables: age, gender, date of recruitment into the sample, tertiary degree completed and having been in long-term unemployment prior to the experiment.
Source: Survey data.

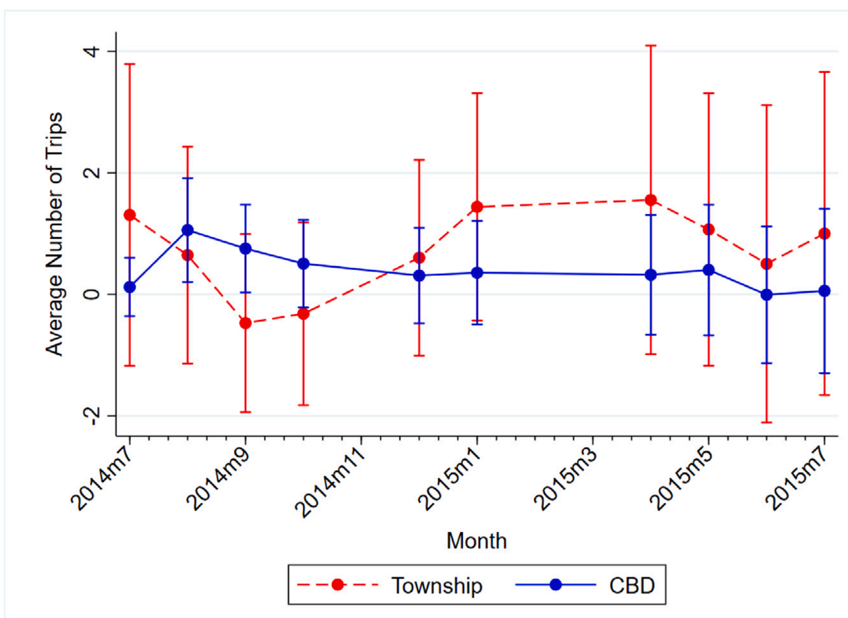


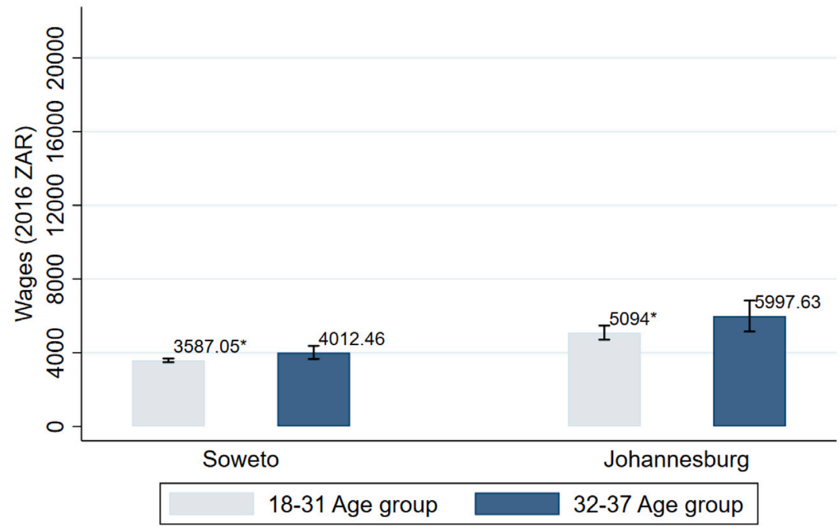
Fig. 8. Search activity of job-seekers in the treatment group who were working in a township job at endline, residualized from baseline covariates.

A back of the envelope calculation that takes account of this divergence in the wage gradients suggests that an individual who has secondary education and is at the median age in our sample, 25, could experience a 40% loss in lifetime income by working in the township as opposed to the city centre.[55]

The job search subsidies appear to have discouraged job-seekers from continuing their search, rendering them more pessimistic and more impatient about their future employment prospects in the city centre,[56] reconciling them to search for lower-paying jobs available in the township. But jobs in the township are also hard to find, which

[55] This calculation is based on the observed salary profiles from Fig. 9, and probably represents a lower bound of the true lifetime earnings as we do not have wage data for individuals older than 37. If we rely on the data from the NHTS, which has a slightly larger sample from 32–48, the income losses for staying in the township are even starker: the choice of staying in the township is associated with a 60% loss in lifetime income. This calculation also assumes that it is harder to get a job in the city centre if you start off with a job in the township. This is a plausible assumption and in line with the reported beliefs by the job-seekers who settled in the township: they now believe that skills are more important than transport constraints in accessing jobs in the CBD so it is less likely that they would transition to a job in the CBD at a later stage in their lives.

[56] Figure A19 in the Online Appendix shows that those who searched more intensively, defined as being above the median distribution of the number



Source: Data from Johannesburg is taken from the 2014/2015 NIDS survey, while data from Soweto was taken from Harambee's 2018 to 2021 employment survey. Individuals with Secondary Education.
*** indicates that p<0.01 and ** indicates that p<0.05 for difference in means tests across Soweto vs Johannesburg. For 18-31, p= 0.0000; for 32+, p= 0.0132.

Fig. 9. Wages in Soweto and in Johannesburg CBD by age cohort.

could explain the overall low levels of employment at endline for the treatment group.

Our findings underscore the importance of the interaction between beliefs about employment prospects and search costs in the context of spatial mismatches. First, job-seekers can be overly optimistic and patient, and hold out for high-paying jobs that they believe match their skills. As a result, they under-search, have distorted beliefs about future jobs and remain unemployed.[57] But learning through interventions that attempt to increase access to jobs may not always be optimal. Once the external constraint is removed through a search subsidy, job-seekers may conclude too soon that their skills are a poor match for the jobs they aspire to if they place too little weight on the overall scarcity of jobs and the noise associated with the search process. As a result, job-seekers who search more intensively can become more pessimistic, more impatient, and may settle for jobs with lower wage gradients.

6. Conclusions

We provide novel evidence on the interaction between beliefs about job prospects and search costs in the context of spatial mismatches between jobs and job-seekers. We show that: (i) job-seekers living in the periphery of large labour markets can significantly overestimate their employment prospects in the city centre due to high transport costs that limit search activity; (ii) job-seekers have distorted beliefs because they overweight the probability that they will get into a high-paying occupation, and they remain patient and optimistic; (iii) reducing search costs partially de-biases job-seekers as they revise downwards their beliefs about wages and about the probability of getting a high-paying job; (iv) job-seekers who search more intensively are more likely to adjust their beliefs, to become impatient and pessimistic and (v) job-seekers who at baseline strongly believe that travelling to employers and dropping a CV is the most effective job search strategy are more likely to adjust their reservation wages and to settle for lower paying jobs in their township.

These findings suggest that transport costs can be an important barrier to the efficient functioning of labour markets, not only because they determine access to jobs but also because they prevent job-seekers from having first-hand experience with the job search, reinforcing distorted beliefs. Removing this constraint through a time-limited transport subsidy can, however, potentially backfire. Transport subsidies can intensify the search period, but if the arrival rate of job offers is overall low, job-seekers may become discouraged and settle too soon for jobs with lower wage gradients outside the city centre. A clear policy implication from our findings is that transport subsidies can have limited effects on employment outcomes, particularly if they are unaccompanied by de-biasing interventions that can better manage job-seekers' expectations, and thus improve targeting in the job search.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2023.103111.

of trips conducted in the first 6 months following the intervention, are more impatient at endline.

[57] This could explain the documented low attachment to the labour market even in contexts of high unemployment (Banerjee et al., 2008).

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