DISCUSSION PAPER SERIES

DP14414

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DEVELOPMENT ECONOMICS

LABOUR ECONOMICS

ISSN 0265-8003

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Discussion Paper DP14414
Published 16 February 2020
Submitted 10 February 2020

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JEL Classification: N/A

Keywords: job search, Biased Beliefs, unemployment

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Spatial Mismatches and Imperfect Information in the Job Search

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February 10, 2020‡

Abstract

Youth unemployment remains high throughout the developing world, at times coexisting with unmet demand for labor and high job turnover. This paper examines one possible explanation: young job seekers who live far from the city centres where jobs are located, over-estimate their employment prospects and underestimate actual commuting costs. Increasing access and exposure to the wider labor market leads job seekers to adjust beliefs and accept jobs closer to home. These findings underscore the importance of supply-side information frictions and how they can lead to spatial and occupational mistargeting in the job search.

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‡We thank Emmanuel Bakirdjian, Nilmini Herath, Akosua Kotareng and Laura Poswell for support with the data collection. Virginia Minni, Tilman Hoenig, Jack Fisher and Michelle Rao provided excellent research assistance. We thank Pedro Bordalo, Joana Naritomi, Diana Weinhold, Gharad Bryan, Rocco Macchiavello and Gabriel Krindler for very helpful comments. This study was approved by the MIT Institutional Review Board and the LSE Ethics Committee, and it was registered in the AEA RCT Registry as project #AEARCTR-0000362.

1 Introduction

Unemployment rates for young job seekers remain staggeringly high across the developing world, particularly in Sub-Saharan Africa. Persistent youth unemployment can pose immediate and long-term economic and social challenges, compromising lifetime earnings, reducing incentives to invest in education, and potentially leading to increased criminal activity. Given rising demographic pressure throughout the developing world, understanding the constraints to youth employment and designing effective labor market policies to remove them remains a pressing policy issue today.

In South Africa, an estimated 54% of the population aged 15-24 reports being unemployed (ILOSTAT 2017). About 82% of the unemployed claim to have been searching for jobs for over a year and approximately 30% have searched for jobs for over 5 years (LMDSA 2015). At the same time, evidence suggests that there is strong demand for labor (Levinsohn and Pugatch, 2014) and that job seekers often turn down jobs, raising the important question of why labor markets do not clear.

A growing literature has attempted to identify the labor market frictions that could explain these figures. One possibility is that the available jobs require more skills than most workers can offer. However, it turns out that labor markets fail to clear even for relatively high-skilled job seekers who have completed secondary and tertiary education (Pritchett, 2000 and Mckenzie, 2014). It is unlikely that the skill mismatch can explain the full story.

Another hypothesis is that there is a mismatch between the kind of jobs that workers are looking for and those that are available. This could explain the very high turnover on jobs even in an environment of high unemployment to the point where firms complain about worker unreliability and unexplained quits (Banerjee et al., 2008). Workers might quit because they over-estimate their chances of getting into more desirable occupations. Such inaccurate beliefs can persist when poor urban infrastructure, high transport costs and residential segregation combine to place low-income groups far from the city center where most jobs are located, which compromises job seekers' ability to search and target jobs effectively. Physical distance can also exacerbate social divides and engender homophily in social and professional networks, thus reducing the accuracy of the information about the labor market that job seekers get from their networks.

While job seekers' beliefs about their future job prospects are central to several labor search models (Diamond, 1982; Mortensen and Pissarides, 1994; Acemoglu and Shimer, 1999; Pissarides, 1985, 2000; Burdett and Mortensen, 1998), all these models have in common the largely untested assumption that job seekers have unbiased beliefs about their employment prospects.

This paper examines how supply-side informational frictions can affect the job search and employment outcomes. In particular, our working hypotheses are that job seekers with limited exposure to the labor market may have biased beliefs about the distribution of wage offers; about the level of skill required for different types of jobs; and about the disutility of commuting to different job locations. These inaccurate beliefs can then lead them to search too little, target the wrong jobs and turn down job offers that are on average higher than the median wage for an employed individual with a similar profile in the area.

We begin by providing empirical evidence on inaccurate beliefs in the job search. We then experimentally vary exposure to the labor market by providing job search subsidies that allow job seekers to offset the costs associated with accessing the labor market in the city centre. Using administrative transport data, we show that the subsidy leads them to search more intensively and more widely. We also observe that searchers update their beliefs in the direction of their true probabilities of employment. Finally, we show that changed beliefs alter the types of jobs job seekers take–they are 81 percent more likely to accept a job in the township where they live. To the best of our knowledge, this is the first paper to trace the entire chain starting from the structure of beliefs, how they change with exposure to the labor market and how changed beliefs affect job seekers' job realizations, in a developing context where informational frictions are likely to be high.

Our study focuses on Johannesburg in South Africa, where transport costs are high and there are sharp spatial divides resulting from a legacy of institutionalized segregation. Most jobs are located in the city center (CBD - central business district), while the majority of low-income job seekers live in townships that are 20 kms away.[1] We gather survey data from a sample of 1,082 job seekers in a large township in the outskirts of Johannesburg, aged between 18 and 32, who have

[1]While the economic and social history of our setting makes these cleavages particularly pronounced, 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., 2018a,b; Franklin, 2017). Our findings are likely to be relevant in other settings characterized by urban sprawl and high transport costs.

completed secondary or tertiary education, and who are actively searching for jobs.

We begin by documenting a striking optimistic bias: 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. We provide suggestive evidence that this bias is driven mostly by an overestimation of the probability of getting into high-paying occupations, as opposed to imperfect information about the level of wages. At baseline, 75% of job seekers reported looking for a professional job, even though the actual probability of an individual with a similar age and skill profile getting a professional job is only 11%.[2] Even those with prior employment experience expect to find a much higher paying job in the future. 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. Consistent with targeting high-paying jobs and being over-confident, job seekers overestimate the probability of getting any type of job–60% of them believe that it is likely or very likely that they will find a job within 2 months, despite having been searching for an average of 15 months.[3]

Our survey also sheds light on why such beliefs might persist. 91% of job-seekers in our sample believe that professional jobs that match their skill and interest are located in the city centre, and that referrals and dropping off CVs in person at firms are the two most likely ways to get these jobs. Since they do not have the social connections, and cannot afford to go often to the CBD, they do not search enough for jobs. Because search intensity is low, learning remains slow.

We then experimentally vary exposure to a wider labor market by providing job search subsidies through smartcards for job seekers to search for jobs in the CBD. The control group received no financial support for the job search. Data on beliefs about entry-level salaries, expectations about jobs, preferences for job types and the location of jobs, and labor market outcomes were collected both at baseline and 12 months after the intervention, thus allowing us to examine relatively long-term outcomes. To observe how the subsidies were used we match survey data to detailed

[2]The official Labor Market Dynamics Survey for South Africa –LMDSA– in 2015 revealed that individuals in the age group 18-32 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 (business or government).

[3]De Bondt and Thaler (1995) and Moore and Healy (2008) document how people can be over-confident, engage in over-placement (the belief that one will perform better than others) and over-precision (the belief that one's information is more precise than it actually is). The idea that there may be misperceptions about employment prospects goes back at least to Manski (1994).

administrative transport data from our partner bus companies that produced the smartcards.

We find that providing job search subsidies led beneficiaries to search more intensively relative to the control group, by traveling more frequently and by covering a wider geographic area in the job search. This increased exposure to the labor market changed job seekers' expectations about the net returns to searching for, and accepting, jobs in the city centre. Twelve months after the intervention, we find that treated job seekers adjusted downwards their salary expectations (5%) and reservation wages (8%). They also revised downward the probability of getting a high-paying job: they were 11 percentage points (an 81% change) more likely to accept a job in their own township, despite having reported a preference for a job in the city center at baseline. Moreover, they reported 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 their own.

While treated job seekers travel farther and longer during the job search, those who have jobs at endline experience lower commuting times relative to the control group. This correlation is consistent with job seekers in the treatment group having learnt more about the pecuniary and utility cost of commuting. Accounting for the pecuniary cost of commuting renders the spatial gradient of wages flat, particularly for those who have only completed secondary education and are unlikely to get a high paying job in the CBD. Adding in the disutility of lost time could make this gradient negative, with jobs in the township dominating. Another explanation is that job seekers with little exposure to the job market over-estimate the possibility of moving from a low-paying job to a better position in the CBD and therefore accept a worse job in the CBD over a better job in the township. Exposure to the labor market may make them more realistic and hence reconcile them to a job in the township.

We find evidence consistent with these learning-based theories. First, those who search more also update their beliefs more. Second, those who at baseline believe that dropping CVs and visiting employment centres in the CBD are the most likely strategies to succeed tend to be those who search more. Finally, the job seekers who adjust their beliefs the most are more likely to take on jobs closer to home.

These findings sit at the intersection of several literatures. The first is a literature that uses experimental methods to rigorously evaluate the impact of labor market search costs, and in particular those resulting from spatial inequality, on employment outcomes in developing countries (Franklin (2017), Abebe et al. (2018b) and Abebe et al. (2019) for Ethiopia).[4] These papers find that transport subsidies help beneficiaries find jobs only in the short-run. Our results are consistent with these and further suggest an explanation for them. In our setting, the stereotypically "good jobs" are likely to have skill requirements that our population lacks. They aspire for these jobs nonetheless and reject jobs that they *can* get. Exposure does not change their chances of getting these jobs but convinces them that high paying jobs are harder to get than they thought.

The second is a literature that emphasizes systematic mismatches between the job quality that job seekers expect and what is available in the labor markets they are searching in (Groh et al 2015, Blattman et al 2016, Beam 2016). In particular Abebe et al. (2019) shows that in Ethiopia job seekers are over-optimistic about their job prospects and that high search costs reduce search for high-skilled job seekers. Abebe et al. (2018a) shows that a job fair improves employment prospects and argues that this is mainly because participants change their perception of available jobs. However, since the job fairs also produce an encouragement and coordination effect (potential employees got to meet other job-seekers) it is not clear if the change in perceptions drives their results. In our case the intervention has no intrinsic reason to change beliefs. Beliefs change due to greater exposure and learning through the job search. Our results are similar as net employment rates do not change, but the employees do become more realistic about the available jobs and may still be better off because, conditional on having a job, they are spending less time commuting.

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 learning is much slower and much more costly in labor markets characterized by informational frictions. We also show that the main

[4] See also Phillips (2014) for the US. Discussions about spatial mismatches leading to unemployment go back to Kain (1992), Holzer (1991) and Zenou (2009).

source of bias is about the most challenging parameter to learn about without physically searching: the probability of getting a job in a high-paying occupation.

This paper also contributes to a literature highlighting the importance of transport infrastructure and urban planning for growthDuranton and Turner (2012); Redding and Turner (2015). We provide suggestive 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 significantly flatten the spatial wage gradient in large cities in the developing world.

Finally, we add to a literature on how biased beliefs of job seekers can affect the optimal design of policies such as unemployment insurance (Spinnewijn, 2015) and active labor market policies (McKenzie, 2017). Assuming correct beliefs about job prospects can bias estimates of the impact of government interventions such as changes in unemployment benefits. Policies to support job seekers in low-income settings categorized by significant asymmetries of information might need to include de-biasing interventions alongside investments in increasing the accessibility of jobs, so as to optimally guide job seekers in the job search and mitigate information-based matching frictions.

2 Empirical setting

The geographic segmentation of South African cities along socioeconomic lines comes as a direct legacy of the Apartheid era and raises several equity and distributional concerns. One such concern is the fact that the main townships, where the majority of the low-income black population resides, are at least 20 km away from the CBD of Johannesburg, where most of the high-paying jobs are located.

High transport costs and distance to jobs may push job seekers into alternative and cheaper search strategies such as relying on friends and relatives to provide information about job opportunities. And yet, spatial inequality is likely to be correlated with social inequality, which can severely restrict the quality of information that job seekers are able to gather through their networks. The inability to access more diverse networks can then lead to the prevalence of biased beliefs about wages, commuting costs and the skills required for accessing different categories of jobs.

We measured beliefs about job prospects for a sample of 1,082 job seekers residing in the township of Soweto, who were listed as actively seeking a job in the Department of Labor's Employment Services (ESSA) database. 98.5% of the Soweto population is black African and for this population employment rates are estimated to be only 35%. Average income is ZAR 2,400 (340 USD), which represents 70% of the median minimum wage in the Johannesburg region. Our sample of job seekers is aged between 18 to 32 years and the majority (83%) has completed secondary education, while a smaller fraction (27%) attended or completed tertiary education. Only 4% of the sample receives unemployment insurance.[5]

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 was 15 months. Most job seekers in our sample appear to be under-searching with limited success: the average job seeker submitted 13 applications in the 5 months prior to the baseline while only about half of the sample attended at least one job interview in the previous 3 years. Monthly transport costs represent over 50% of reported monthly income and 11% of the median monthly wage observed in labor surveys (LMDSA) for the region.

The majority of job seekers are looking for a professional job in business or in the financial sector, followed closely by government jobs.[6] Conversion rates from applications to interviews and from interviews to jobs are, on average, extremely low (10%), suggesting that job-seekers are targeting jobs that they are not qualified for.

Approximately 12% of the sample reports turning down a job in the previous 3 months, 63% of which were in sales.[7] Low pay and distance are among the top three reasons for turning down a job.[8]

The majority of 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, mostly because travel costs would be lower. Consistent with these beliefs, close to

[5]This income represents 33% of the average monthly income reported at baseline. See Tables 1 and 2 in the Online Appendix for descriptive statistics.

[6]Figure 1 in the Online Appendix.

[7]Those who have been searching longer are more likely to have turned down jobs in the past as shown in Figure 2 in the Online Appendix.

[8]Figure 3 in the Online Appendix.

half of the sample identifies transport as a key obstacle to employment, ahead of the lack of skills.[9]

About 51% of the sample reports that submitting CVs online is their main strategy for seeking employment. While only 36% of the sample reports being able to visit employers, 61% of those who do so believe that this strategy is likely or very likely to result in an interview.

3 Main Findings

3.1 Imperfect Information

We begin by documenting that job seekers are over-optimistic about their job prospects. We measure actual wages in the Gauteng area (Johannesburg and neighboring Pretoria) using data from the LMDSA (2015), for a sample similar to ours consisting of employed individuals with secondary school degrees, aged 18 to 32. When we compare these figures to reported expected salaries in our survey we find that approximately 90% of job seekers hold positively biased beliefs about average wages.[10] Given that the median actual wage is approximately 3,000 ZAR (424 USD), at the midpoint of the distribution, job seekers expect to receive almost three times more.

We then try to unpack the main source of this bias. This sizable 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. Median expected earnings for jobs that can traditionally also be found in the township (manufacturing, sales and construction) are close to actual median monthly earnings reported in the LMDSA, but for jobs that are usually found in the city centre (government and business), job seekers, in fact, underestimate entry wages.[11]

[9] Figure 4 of the Online Appendix.
[10] Figure 5 in the Online Appendix.
[11] Monthly earnings for all job categories are shown in Figure 6 of the Online Appendix.

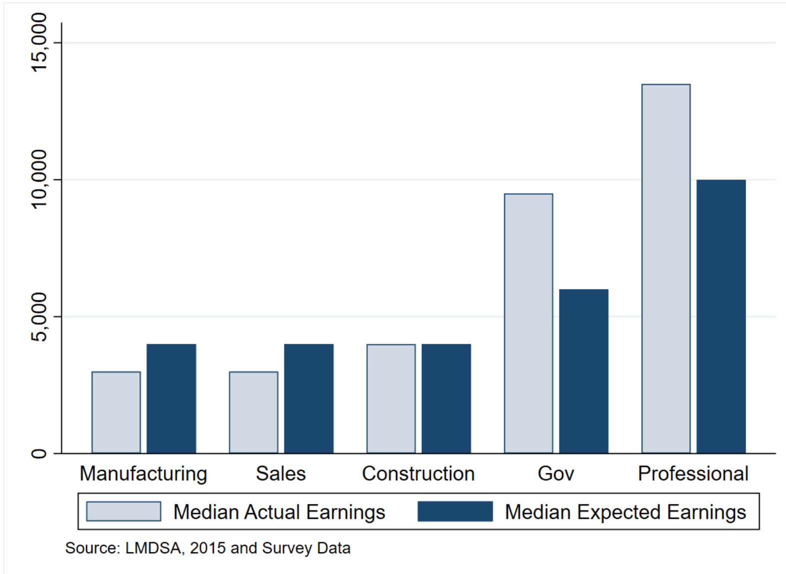

Figure 1: Expected vs Actual Median Monthly Earnings (ZAR).

Given that job seekers appear to hold close to accurate beliefs about the wage distribution, we calculate the implicit probability that each job seeker attributes to getting access to a high-paying job. 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. We solve for probability P and compare this implicit probability of getting a high-paying job to the actual probability observed in the LMDSA. 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 5% of job seekers hold an accurate belief about the actual probability of getting a high paying job, while over 50% believe this probability to be 10 times higher than it actually is.[12] This might be because it is easier to learn about prevailing wages than to learn the specific probability that one can get a job that is stereotypically associated with high pay in the CBD (Bordalo et al 2016), the wealthiest city in Sub-Saharan Africa.[13] Consistent

[12]Figure 7 of the Online Appendix.

[13]Similarly, Figure 8 in the Online Appendix shows that for those who were employed in the past, wage experience is uncorrelated with biased beliefs about future prospects at baseline.

with the interpretation that the source of bias lies in their perceptions about accessing a high-paying occupation, we find that job seekers in our sample are overconfident about their own job prospects (Benoît et al. (2015) and Moore and Healey (2008)). They expect to earn higher salaries on average relative to others in the township with similar levels of education.[14]

Taken together, the evidence suggests that job seekers appear to be unemployed but optimistic, overconfident and patient. They identify transport as a major barrier to finding employment and as a result, rely heavily on their social networks to obtain information about the job market. These networks are composed of individuals residing in the same township with similar levels of education. This kind of homophily can then significantly exacerbate errors in beliefs (Kets and Sandroni, 2016).

3.2 Experimental Evidence

To test whether job seekers adjust their expectations in the direction of their experience, our experiment induced a subset of job seekers to expand their geographic search area and to search more intensively for jobs. We provided 365 individuals (out of 1,082) with a transport subsidy that could only be used for transport, and another 352 individuals with a general job search allowance. The latter subsidy was not restricted to transport but beneficiaries were primed to think about the importance of job search costs when they received it. We partnered with the main bus system connecting Soweto to Johannesburg's CBD to produce smartcards that would allow us to observe how the subsidy was used between transport and other expenses.

The transport subsidy and the unconditional job search subsidy were calibrated to represent a similar monetary transfer of ZAR 500 (36 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), with the one difference 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 smartcard, loaded with a single return trip.[15]

We begin by examining patterns of subsidy usage across the two treatment groups. Adminis-

[14] Figure 9 in the Online Appendix.

[15] The control group was not more likely to report losing the card, mitigating concerns about measurement error.

trative data revealed that job seekers who received the unconditional job search allowance spent the majority of it on transportation (close to 70%, as shown in Figure 11 in the Online Appendix). As a result, for the rest of the analysis, we focus on the effect of either treatment. We begin by estimating the impact of the job search subsidies on beliefs and employment outcomes through the following equation:

$$Y_i = \alpha + \beta * AnyTreatment + X_i + \epsilon_i \tag{1}$$

where Y_i represents our key outcomes of interest for individual i such as expected salary, reservation wage, and employment outcomes. 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 and the date in which the individual was assigned to the different treatments during the randomization.[16] Take up of the smartcards was high (84%).[17]

Table 1 presents our first set of experimental findings where we pool the two treatments. We find that 12 months later, the probability of being employed and average earnings are not improved by the intervention.[18]

Column 4 shows that both treatment and control are equally unlikely to find their preferred professional job.[19] Only 13% of job seekers in our sample are employed in a professional job (high-skill) even though this was the main target of their job search.[20]

Column 5 reveals that those who received financial support for the job search were 11 percentage points more likely to accept jobs in their own township, which represents an 81% increase from the control group mean. Interestingly, monthly earnings net of reported transport costs are not

[16]Treatment and control groups are balanced on several relevant characteristics and attrition was both low at 9.8% (from an original sample of 1,200 job seekers) and balanced, as shown in Sections 5 and 6 of the Online Appendix.

[17]Section 8 of the Online Appendix shows unsurprisingly that the treatment on the treated results are larger in magnitude.

[18]The lack of impact of the job search subsidies on the extensive margin of employment is in line with evidence from (Abebe et al., 2018a).

[19]Skill level is measured in an increasing scale of 1 to 3 and corresponds to the three skill categories defined by Statistics South Africa. High skill includes managers, technicians and professionals. Medium skill includes clerks, sales and services. Low skill includes elementary and domestic workers.

[20]These figures are in line with the occupational distributions observed in LMDSA in 2015, where only 11% of the sample is working in a professional occupation, 21% hold jobs in retail (medium skills), 25% are in elementary occupations (low skill) and 14% in crafts (low skill). Source: LMDSA (2015). The full breakdown is shown in Figure 12 in the Online Appendix. This evidence suggests that our sample is representative of this demographic group.

Table 1: Employment and Beliefs

	Employment						Beliefs			
Dependent Variable	**Probability of Employment**	**Jobs Since Baseline**	**Is Currently Employed**	**Skill level**	**Job in Township Conditional on Job**	**Mean Monthly Income Net of Transp Costs Cond on Job**	**Log Reservation Wages**	**Log Expected Wage**	**Nbr Days needed to find another job**	**Time Discount**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment	0.018	0.037	-0.005	-0.036	0.107	-184.312	-0.077	-0.051	34.039	338.241
	(0.026)	(0.051)	(0.041)	(0.064)	(0.034)	(225.854)	(0.033)	(0.023)	(15.058)	(174.723)
Controls										
Age	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Gender	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Length of Job Search at Baseline	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean Dep Var Control	0.741	0.901	0.529	1.859	0.14	3538	8.436	8.747	146	2270
Std Dev Control	0.439	0.978	0.500	0.614	0.348	2017.4	0.486	0.567	202	2099
Observations	935	1,081	697	623	619	668	977	1,078	1,060	1,072
Adjusted R squared	0.050	0.050	0.050	0.020	0.05	0.05	0.038	0.020	0.010	0.012

statistically different across groups (column 6) suggesting that commuting costs might offset any premium associated with a job in the CBD.

Columns 7 through 10 confirm that job-seekers respond to the treatments in a way that is consistent with the presence of informational frictions at baseline. Increased exposure to the job market is associated with an 8% reduction in reservation wages and a 5% reduction in their expected future wage. Job seekers who benefited from the subsidy also updated their beliefs about the value of employment: they believed that if they had a job and lost it, it would take them 34 days longer to be able to find another job. This suggests that exposure to the wider labor market significantly reduced the extent of the biased beliefs that job seekers held and made them more pessimistic about the job search.

On the potentially negative side, we find that the intervention also appears to have led job seekers to more heavily discount the future: 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 11).[21] This is consistent with theories on the interaction between pessimism about the future and present bias,[22] and raises the possibility that the treatment group is more willing to settle for jobs with lower salary growth gradients.[23]

Those with the highest bias at baseline update their reservation wage the most.[24] Note that consistent with Krueger and Mueller (2016), individuals do not fully update and prior biases persist.

4 Mechanisms

4.1 Intensifying the Job Search

How did the subsidies affect job search effort? Administrative data shows approximately 3.5 times more trips for both treatment groups compared to control (figures 15 and 16 in Online Appendix). That this holds even for the unconditional group suggests that job seekers really believe that

[21] Measured as how much they would need to receive in 5 weeks' time to forego 300 rand today.

[22] E.g. Banerjee and Mullainathan (2010) Bartos et al. (2018) show experimental evidence suggesting that feeling poor makes people more present-biased.

[23] DellaVigna and Paserman (2005) have analyzed theoretically how impatience can affect job search behaviour and Munasinghe and Sicherman (2000) show that more impatient job seekers settle for jobs with flatter wage profiles.

[24] Figure 13 of the Online Appendix.

searching in the CBD is likely to get them a job. Column 1 of Table 2 shows that subsidy recipients travelled farther (in kms) from their home address and column 2 that they spent more time travelling.[25] These findings confirm that the subsidies enabled job seekers to gain access to a geographically wider labor market and to engage in their preferred strategy of dropping CVs to firms in the CBD.[26]

We find no evidence that inducing job seekers to spend more time traveling crowded out other job search activities (see columns 3 to 7).[27] 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 (approximately 20%).

4.2 Learning about job prospects and commuting costs

Travel in search of jobs might have exposed job seekers in the treatment group to additional information about wages, the probability of job offers and commuting costs. Consistent with this, our first finding is that those who update their beliefs the most are those who at baseline believe that job search activities that required transport such as visiting job centers and dropping off CVs were the most likely to succeed.[28]

Following Chernozhukov and Hansen (2008) and Machado and Santos Silva (2018), we use an instrumental variable quantile estimator to examine whether job seekers who travelled the most are also the ones who are most likely to choose a job in their own township. Given selection into the log total number of trips job seekers engaged in, we instrument this variable with assignment to treatment. Restricting our sample to those who have a job at endline, the job seekers who were at the 75th percentile of the distribution of the number of trips completed were 3 percentage points

[25] These samples are restricted to participants who used their cards during the study. Table 13 in the Appendix shows that there is balance between treatment and control groups in this restricted sample.

[26] A modal trip length of 52 minutes corresponds to trips to the CBD. Figure 16 in the Online Appendix shows that treated job seekers also travelled more in the secondary bus line that could get them from the CBD to neighboring business areas.

[27] The subsidy increased both transport and non-transport job search activity, suggesting that treated job seekers were overall more engaged with all the job search strategies they could pursue. These included dropping CVs, registering in employment centres, submitting CVs online and asking friends for referrals. Figures 17 through 19 in the Online Appendix.

[28] Table 5 in the Online Appendix. The interaction effect corresponds to a 3 percentage point reduction in the expected salary over the control mean.

Table 2: Job Search Effort

Dependent Variable	**Log Total Distance between Home and Areas Travelled to (Km)**	**Average Modal Travel Time (min)**	**Log Number Applications to Jobs**	**Log Number of Interviews**	**Conversion App. to Interviews**	**Conversion Interviews to Jobs**	**Log Job Offers**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	2.598	15.940	0.092	0.071	-0.030	-0.011	0.015
	(0.160)	(5.112)	(0.084)	(0.050)	(0.026)	(0.018)	(0.041)
Controls							
Age	Y	Y	Y	Y	Y	Y	Y
Gender	Y	Y	Y	Y	Y	Y	Y
Length of Job Search at baseline	Y	Y	Y	Y	Y	Y	Y
Mean Dep Variable Control Group	4.177	52	2.268	0.704	0.205	0.186	0.438
Std Dev Control Group	2.464	33.34	1.140	0.687	0.412	0.299	0.507
Observations	793	542	937	946	898	899	580
Adjusted R squared	0.257	0.006	0.162	0.044	0.025	0.011	0.006

more likely to have accepted a job in the township.[29]

We plot the correlation between job seekers in each experimental group who adjusted their salary expectations the most (defined as above the mean of the distribution) against the probability of accepting a job in the township. Job seekers who adjusted their expectations the most in the treatment group are significantly more likely to accept a job in the township (Figure 20 in the Online Appendix).

We then examine what type of learning could explain the observed change in employment decisions and beliefs. We recompute the implicit probability of getting a high paying job using expected salaries at endline, following the strategy used in section 2. In Figure 2, we compare the implicit probabilities at baseline and at endline: the cdf of the probability of getting a high paying job shifts to the left at endline, confirming that treated job seekers revised downwards their expectations about their job prospects.

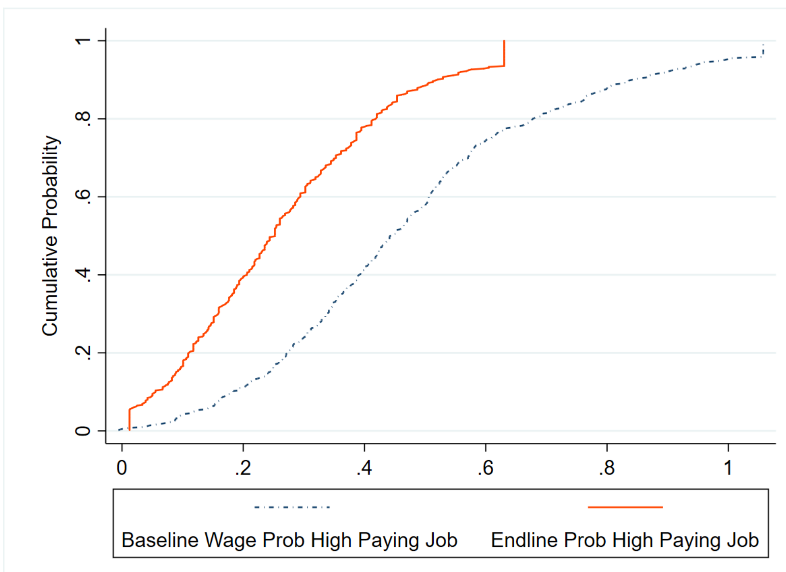

Figure 2: Cumulative implicit probabilities of getting a high paying job, before and after the job search intervention.

There are two additional mechanisms which could generate the observed correlation between traveling more during the search phase and taking a job closer to home. First, intensive travel

[29]Table 6 in the Online Appendix.

may have exposed the searchers to the disutility associated with commuting. While jobs seekers might already know the cost of bus fares, they could under-estimate the time costs associated with frequent bus travel or the increased cost of amenities associated with a CBD job. Second, a more intensive job search process may have made the job seekers more sensitive to the costs of commuting by persuading them that the jobs they are likely to get in CBD are not that much better paid than the ones they can get in the township. Both of these would make them more inclined to take a job closer to home.

Figure 3 shows the monthly wages of respondents reporting to have a job at endline. The left panel presents the monthly earnings net of reported commuting costs while the right panel shows gross monthly earnings. The data are further broken down by those holding jobs in the city centre versus the township, and by level of education (secondary and tertiary), the latter being the strongest predictor of the wage level. The spatial wage premium of working in the CBD is fully offset by pecuniary commuting costs, particularly for those holding only a secondary schooling degree.[30]

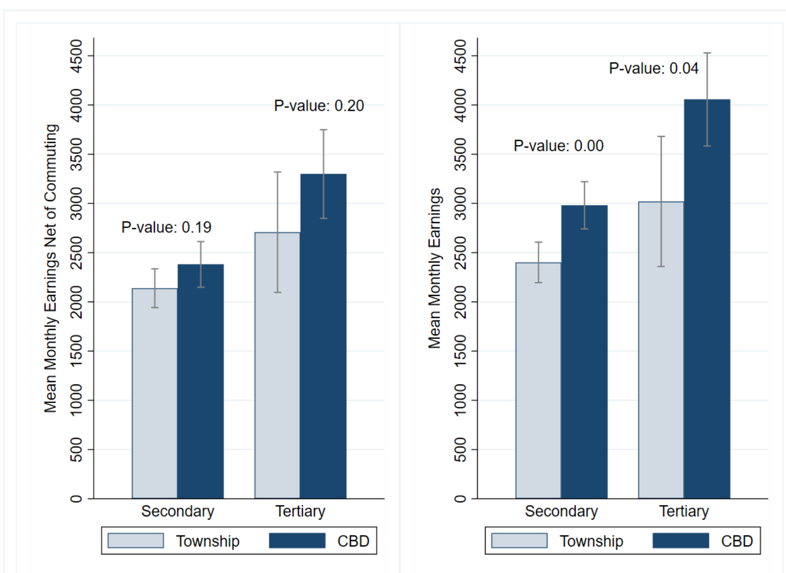

Figure 3: Monthly Earnings and Commuting Costs
Source: Survey Data and Administrative Transport Data

[30]These findings are similar when we place on the y-axis earnings residualized from baseline covariates (Online Appendix Figure 21).

Accounting for the time and utility costs of commuting could make the differences between earnings in the CBD and in the township observed in Figure 3 even smaller.[31]

5 Conclusions

This paper provides novel evidence on how imperfect information can shape the job search and determine employment outcomes of young job seekers. We provide evidence that: i) job seekers living in the periphery of large labor markets can significantly overestimate their employment prospects in the city centre due to high transport costs that limit search activity; ii) job seekers have biased beliefs because they overweight the probability that they will get into a high-paying occupation; iii) increasing exposure to the wider labor market partially de-biases job seekers as they learn that the wage premium in the city center is small and likely to be offset by higher commuting costs; iv) job seekers who adjust their beliefs are more likely to settle for jobs in their township, report lower reservation wages and expected salary, and become less confident in their ability to find a job quickly.

These findings suggest that transport costs can be an important barrier to the efficient functioning of labor markets in the absence of other mechanisms for providing accurate information to job-seekers. Future research should attempt to understand the longer-term consequences of learning through the job search.

[31] The reported average monthly commuting costs in our endline survey for those working in the CBD was approximately 550 ZAR (37 USD) per month. In the administrative transport data we observe that the median length of the trips conducted by an individual who reports having a job at endline in the CBD is approximately 42 minutes. Taking the median wage in the CBD as being 3,000 ZAR (LMDSA, 2015), the hourly costs of commuting in the form of foregone income would be 24 ZAR per day, or approximately 524 ZAR per month. Effectively, accounting for the time costs associated with travel to the city centre would double the actual commuting costs, making city centre jobs even less desirable. Note that this may still underestimate the costs associated with a job in the CBD if the local amenities in the CBD are also more expensive.

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Online Appendix for

Spatial Mismatches and Imperfect Information in the Job Search: Evidence from South Africa

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(Not for Publication)

February 9, 2020

1 Empirical Setting: Descriptive Statistics

Table 1 shows the demographic and household characteristics of our sample of 1,082 job seekers in the Soweto township, outside of Johannesburg, while Table 2 shows their employment and job search history.

Table 1: Job Seeker Household Characteristics at Baseline

	Mean	Std	Min	Max	N
Age of Job Seeker	25	3	18	32	1,082
Completed Secondary Education	0.83	na	0	1	1,082
Attended or completed tertiary education	0.27	na	0	1	1,082
Number of household members	4	2	1	15	1,082
Share of employed members among hh member 18-65	0.27	na	0	1.00	1,082
Total Income, previous month (ZAR)	622	1241	0	7300	1,077

Source: Survey Data

Table 2: Job Search and Employment History

	Mean	Std	Min	Max	N
Worked between 2011 and 2014	0.57	na	0	1	1,082
If worked, number of jobs	1.46	0.80	1	10	679
Number of job applications in the last 5 months (*win*)	12.69	19.18	0	100	1,082
Number of months looking for a job	15.35	16.60	0	168	1,082
Job Interview in the last 36 months	0.51	na	0	1	1,081
Avg. monthly job search related transport expenses	341	290	0	1130	1,082
Avg. monthly job search related expenses (non-transport)	195	394	0	2675	1,082

Source: Survey Data *Win* means winsorized at the 5% level.

The majority of job seekers are looking for a professional job in business or in the financial sector, followed closely by government jobs as shown in Figure 1.

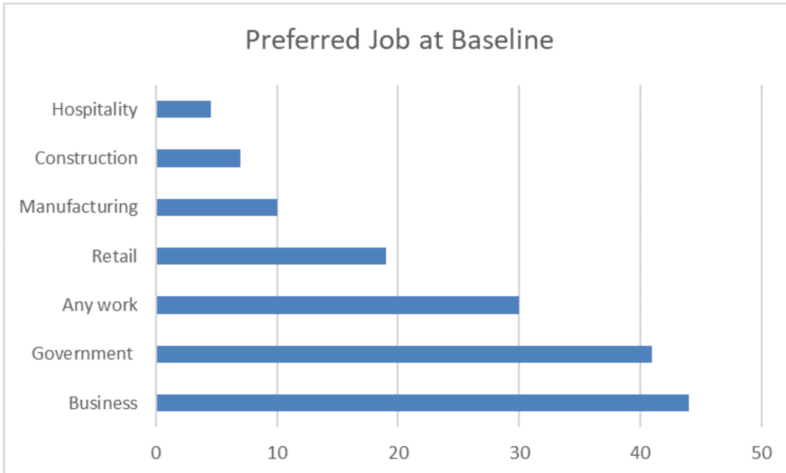

Figure 1: Preferred sector of employment.

Note: Respondents identified all the jobs they were interested in so the values do not add to 100%. Source: Survey Data

Interestingly, approximately 12% of the sample reports having turned down a job in the previous 3 months, 63% of which were in sales. Figure 2 reveals that those who have been searching for longer are more likely to have turned down jobs in the past, which could allay concerns of negative selection into long-term unemployment in our sample.[1]

[1] 90% of those in our sample have been searching for longer than 3 months.

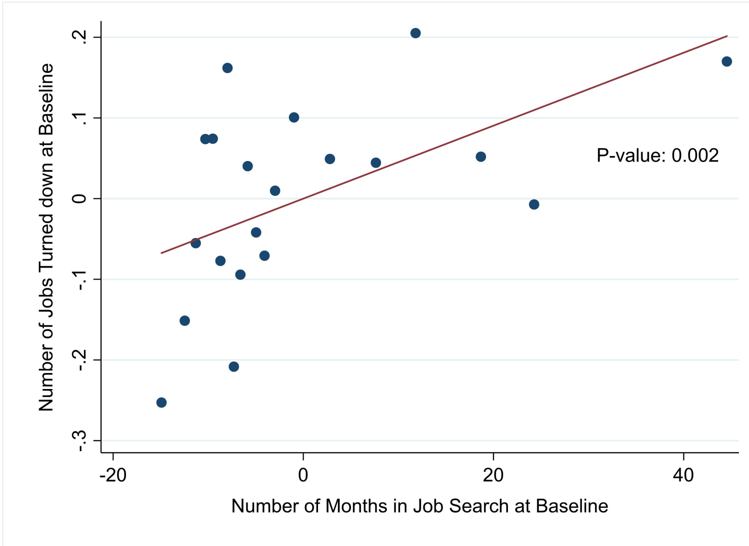

Figure 2: Length of the job search and number of jobs turned down. Values are residualized from the following variables: age, gender, date of recruitment into the sample and length of the job search at baseline. Source: Survey Data

Figure 3 shows that low pay and distance appear to be among the top three reasons for turning down a job.

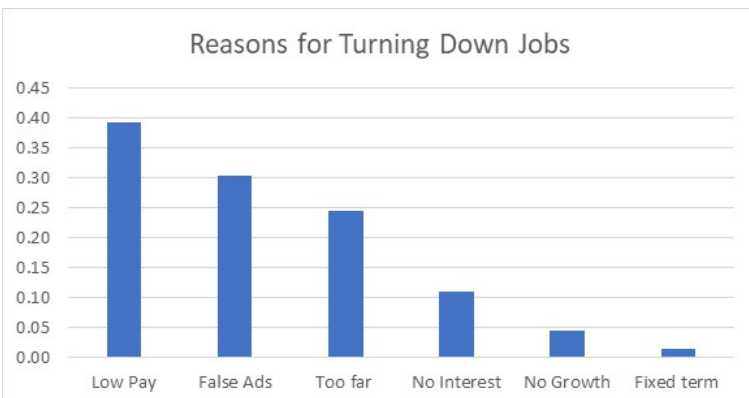

Figure 3: Reasons for turning down interviews and jobs in the previous 3 months.
Source: Survey Data

At baseline, the majority of job seekers in our sample (91%) believes 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. Consistent with these beliefs, close to half of the sample identifies transport as a key obstacle to finding employment, ahead of the lack of skills, as shown in Figure 4. Specifically they seem to believe that if they could physically search more intensively in the CBD they would succeed in getting a high-paying job.

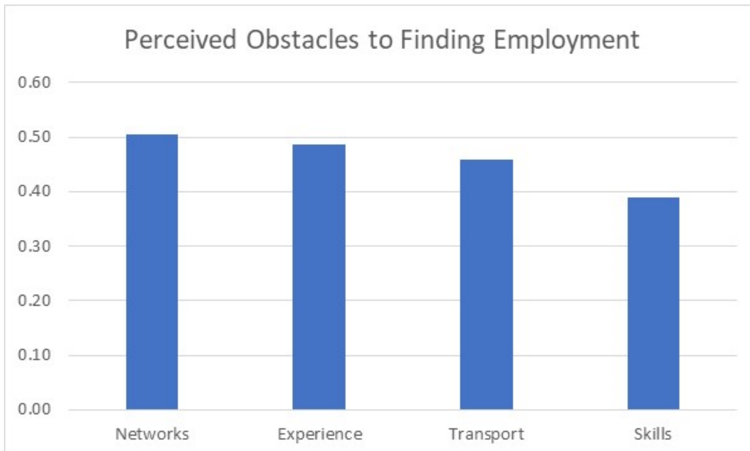

Figure 4: Perceived Obstacles to Finding Employment

Source: Survey Data

2 Imperfect Information: Misperceptions about Employment Prospects

Figure 5 reveals that approximately 90% of job seekers hold positively biased beliefs about average wages.[2] Given that the median actual wage is approximately 3000 ZAR, at the mid-point of the distribution, job seekers expect to receive almost three times more than that.

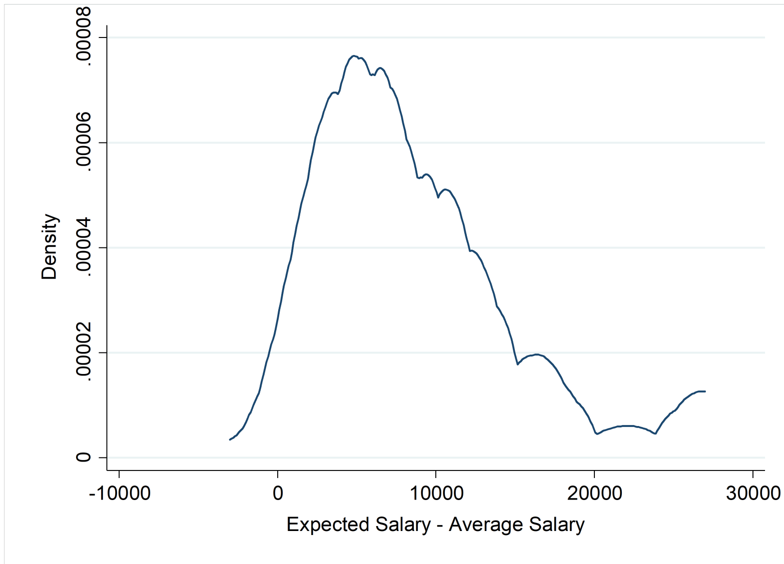

Figure 5: Salary Bias at Baseline (Expected vs Actual Median Wage).

Note: The distribution of wedges in expected own salary and the actual median salary for employees with a similar educational and age profile. Source: Survey Data and LMDSA 2015

Figure 6 shows average salaries for individuals in a similar age group to those in our sample and with a similar skill set (LMDSA 2015). Note that those who end up in professional or government jobs can earn monthly wages that are up to four times higher than the median wage of the distribution, which is marked by the horizontal red line (3000 ZAR, approximately 425 USD).

[2]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.

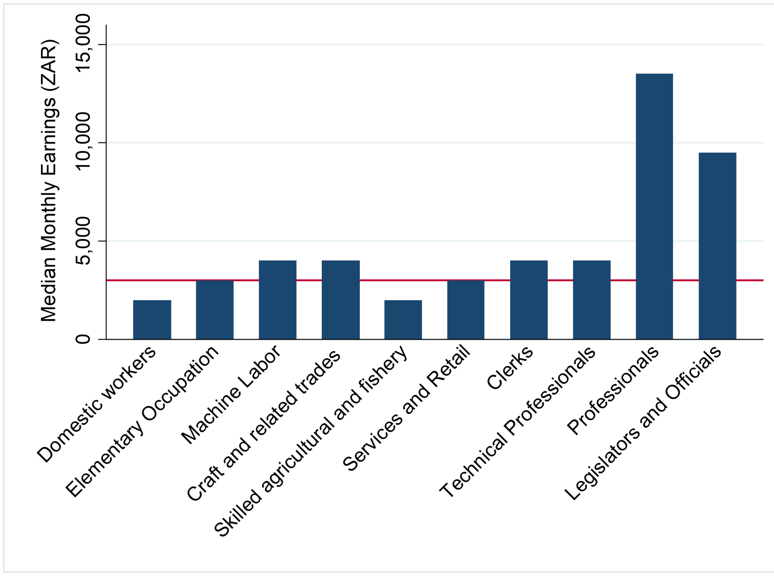

Figure 6: Actual Monthly Earnings (ZAR).

Note: The reference line corresponds to the median wage in the distribution at 3,000 ZAR. Only 11% of the sample has a professional job. Out of the largest categories of employment, 21% hold jobs in retail, 25% are in elementary occupations and 14% in crafts. Source: LMDSA 2015

Figure 7 shows the cumulative probability distribution for P, for those reporting to target professional and government jobs.[3] The vertical reference lines in each graph report the actual probability of obtaining each of the jobs according to the LMDSA. 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.

[3]We cannot disentangle the implicit probability for a professional vs a government job but these two categories of jobs appear to be similar in expected and actual salary.

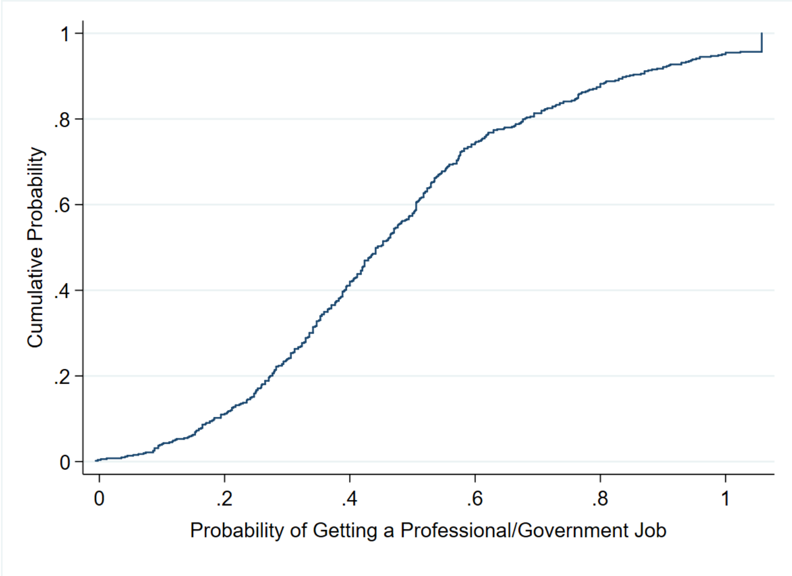

Figure 7: Cumulative Probability Distribution for the Probability of Getting a Professional or a Government Job.

Importantly, the 57% of our sample that reports having had at least one job in the three years prior to the baseline, also reports having received on average 3000 ZAR (approximately 425 USD) as monthly earnings which is exactly the figure we observe as the median salary in LMDSA that same year. In other words, the bias does not come from never having had a job and therefore having no idea of the wage. Job-seekers who have an accurate idea of the going wage for accessible jobs are also excessively optimistic about their ability to receive a job offer in a higher paying occupation in the future. In Figure 8 we show that wage experience is not correlated with biased beliefs about future salaries at baseline.

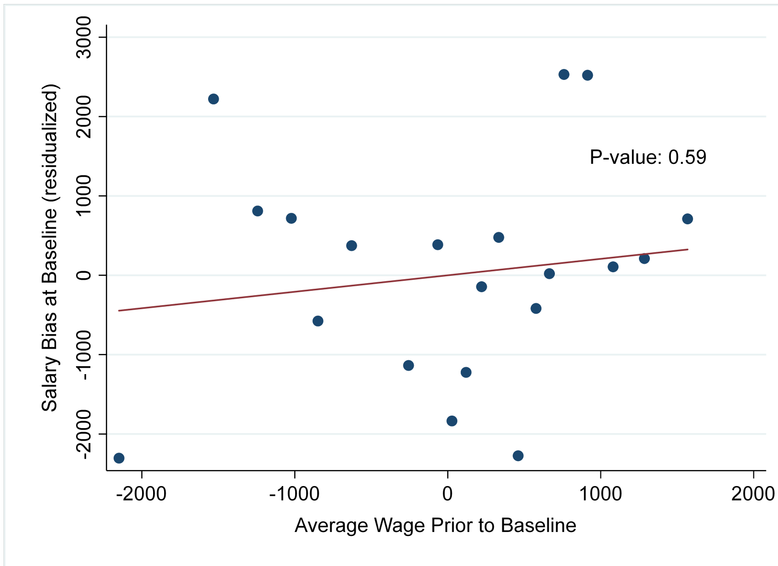

Figure 8: Salary Bias at Baseline and Wage Experience Prior to Baseline

Job seekers in our sample appear to also be overconfident about their job prospects.(Benoit et al 2015 and Moore and Healey 2008). Figure 9 shows that job seekers expect to earn higher salaries than others in the township with similar levels of education.

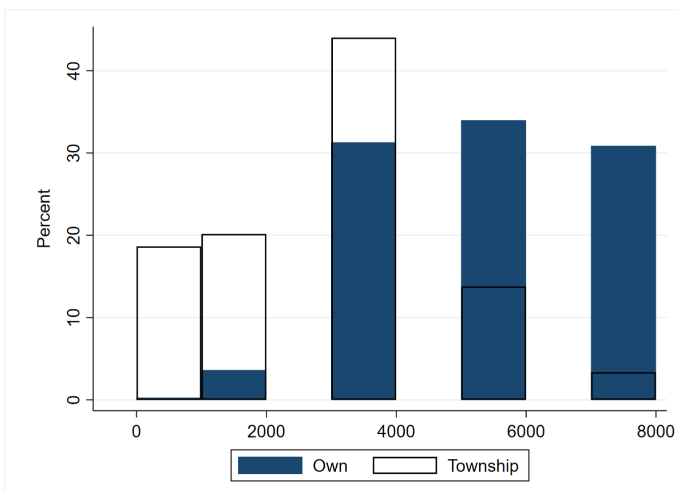

Figure 9: Wedge in Expected Salary - Own vs Township Average.

Note: The distribution of wedges in expected own salary and the expected salary for others with a similar educational profile who live in the township. Source: Survey Data

In principle, it is possible that an important additional supply-side reason for high unemployment is that job seekers are discouraged by the length of time they have been unsuccessfully searching for jobs. The evidence from our baseline survey is not, however, consistent with this hypothesis. In fact, the majority of job seekers appear to be overly confident at baseline about their skills and about their ability to find a job in their preferred sector of employment. 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. Another possible reason why they don't find jobs is that they are too impatient and therefore unwilling to put in the effort it takes to get a job (DellaVigna and Paserman 2005, Munasinghe and Sicherman 2000). However job seekers in our sample do not appear to be particularly impatient: 62% report preferring to get ZAR 200 (approximately 18 USD) in a month's time rather than ZAR 100 (approximately 9 USD) today.

An important hypothesis in our study is that high transport costs and the geographic distance to jobs may lead to an over-reliance on social networks to obtain information about the job market. If these networks are mostly localized, and the labor market is heavily segmented, then job seekers will have limited exposure to accurate information on market wages and on the probability of getting different types of jobs in labor markets that are farther away. Consistent with the hypothesis that information provided by social networks is a key driver of beliefs and behavior during the job search, over 60% of our sample considers talking to friends as their primary source of information on the job market.[4] Figure 10 shows that friends are the main source of advice on the job search.

[4]These findings are in line with previous evidence from the South African Social Attitudes Survey (SASAS, 2014), which found that a majority of unemployed people search for jobs by asking friends and relatives for information and support (51%). Note also that the impact of social networks on job search intensity and labor market outcomes goes beyond the transmission of information on job opportunities and prevailing market wages. It is also possible that social networks create social pressure, implicit or explicit, for medium-skilled job seekers to seek high-paying occupations. Consistent with this hypothesis, 84% of respondents in our sample believe that if they were to get a job, it would make people in their network more likely to get a job, either because they would be able to support them financially or because they would represent an important role model. When asked to identify the three people who would directly benefit from their support if the participants in our study were to find a job, the majority of the sample identifies friends who live within a 5-15 minute car ride from their homes.

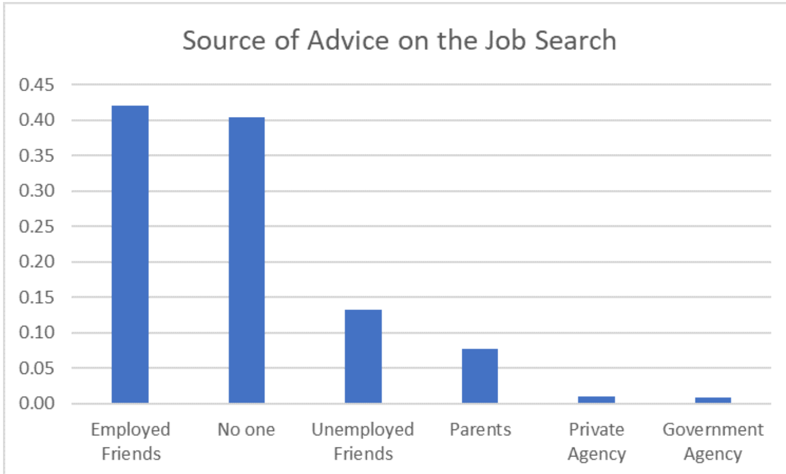

Figure 10: Source of Advice on the Job Search. Source: Survey Data

3 Experimental Evidence: Impact on Employment and Beliefs

In Figure 11 we use administrative data from our partner transport company to show that job seekers who received the unconditional job search allowance spent a large majority of it on transportation (close to 70%). In fact, the share of expenses registered on the smart-cards made on transport increased consistently over time. Almost one year after the endline survey, the share of expenses on the smartcards that were allocated to transport came close to 80-90%.[5]

[5]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 behavior more than 12 months after the end of our experiment.

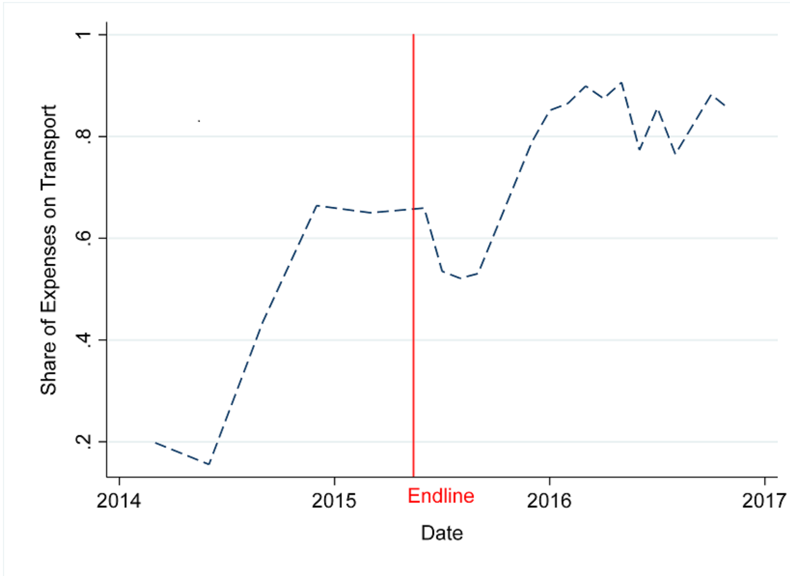

Figure 11: Share of Transport Expenses in Unconditional Treatment

Source: Administrative Transport Data

As seen in Figure 12, only about 13% of jobs seekers in our sample are employed in a professional job despite the fact that a professional job in business was the main target of their job search.[6]

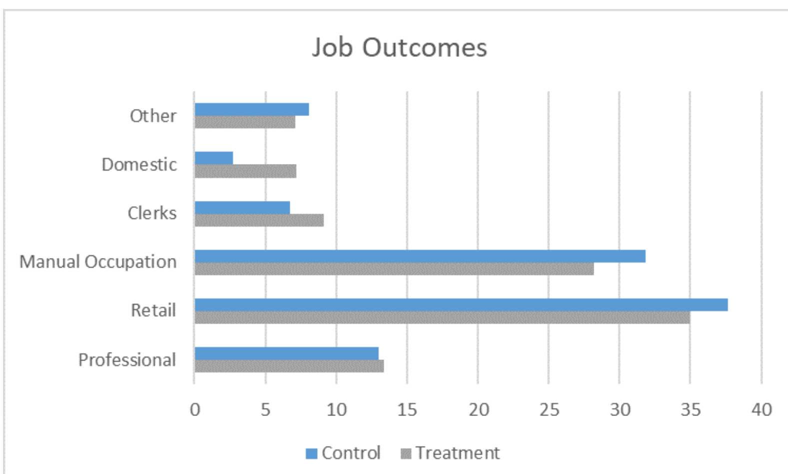

Figure 12: Employment Outcomes by Job Type.

Source: Survey Data

Figure 13, shows that those with the highest bias at baseline update their reservation wage

[6]These figures are in line with the occupational distributions observed in other datasets such as the Labor Market Dynamics Survey in South Africa (LMDSA) in 2015, where only 11% of the sample is working in a professional occupation, 21% hold jobs in retail, 25% are in elementary occupations and 14% in crafts. Source: LMDSA (2015)

more as a result of treatment. This can be seen through an inward shift of the treatment curve, resulting in a steeper decline of the reservation wage at endline for those who start off with more biased beliefs. Note however that the slope of the updating curve is flatter than the 45 degree line indicating that individuals do not fully (one-to-one) update in response to the information obtained through the experiment. Prior biases still persist, which is consistent with previous 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 prospects.

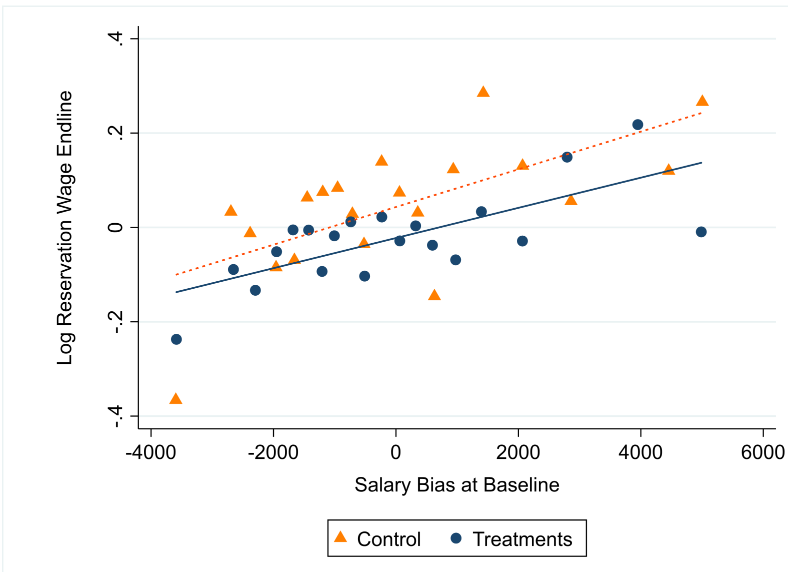

Figure 13: Salary Bias at Baseline and Reservation Wage at Endline.

Note: Values are residualized from the following variables: age, gender, date of recruitment into the sample and length of the job search at baseline. Source: Survey Data

Given the baseline heterogeneity in job search and employment experience reported in Table 2, we now examine whether prior exposure to the labor market is a substitute or a complement to the new learning that occurred during our experiment. Table 4 shows that those with prior work experience are more likely to update their beliefs during the intervention. However, previous work experience does not seem to differentially influence the decision to work in one's township.

Similarly, we examine whether previous wages anchor job seekers' beliefs about future wages. At baseline, the level of previous wages does not appear to determine the level of salary bias reported by respondents (defined as the difference between expected salary and the average salary in the market).[7] Job seekers with job experience do not appear to anchor their reservation wages to past wages. This relationship is illustrated in Figure 14 below.

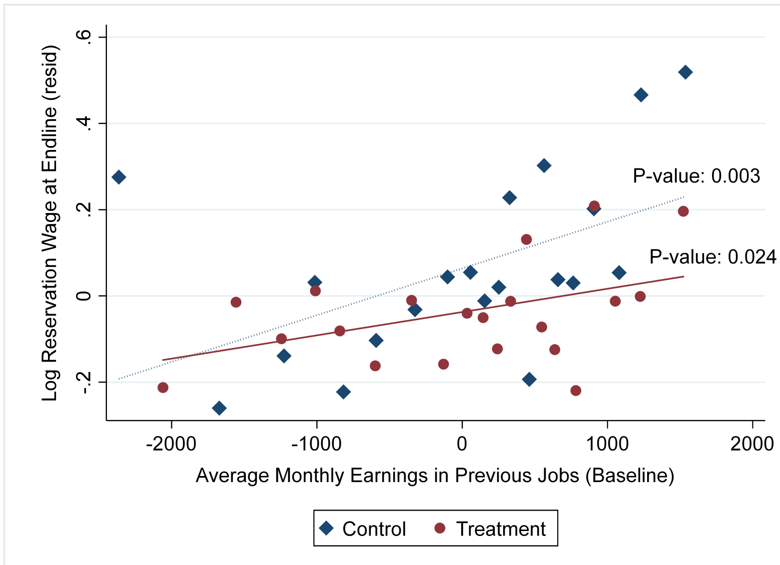

Figure 14: Reservation Wage at Endline and Average Monthly Earnings prior to Baseline

Note: Values are residualized from the following variables: age, gender, date of recruitment into the sample and length of the job search at baseline. Source: Survey Data

4 Mechanisms

4.1 Intensifying the Job Search

The administrative transport data from the smart-cards distributed during our intervention reveal that both treatment groups travelled more in search of jobs. Figure 15 shows that during the experiment, both treatment groups travelled more frequently in the main bus line between Soweto and CBD. Figure 16 shows that treated job seekers also travelled more in the secondary bus line (identified as Metrobus) that could get them from CBD to other economic hubs in the greater Johannesburg area. This is in line with the fact that job seekers believed that most jobs were in the city centre and that dropping CVs in person was one of the most effective job search strategies

[7] While we do not have more detailed information on whether their previous work experience was in the local labor market or in the city centre, it is likely to have been the former.

Table 4: Heterogeneity in Exposure to the Labor Market

Dependent Variable	**Log Reservation Wages (1)**	**Log Expected Wages (2)**	**Nbr Days needed to find another job (3)**	**Salary Bias (4)**	**Present Bias (5)**	**Job in Township Conditional on job (6)**
Treatment	-0.011	0.076	67.398***	481.432	138.597	0.084***
	(0.050)	(0.067)	(22.308)	(331.074)	(238.898)	(0.025)
Treatment * Worked Previous 3 Years	-0.114*	-0.220**	-57.963*	-1,376.126**	348.801	-0.013
	(0.065)	(0.096)	(30.219)	(520.176)	(267.761)	(0.041)
Worked Previous 3 years	0.063	0.152	26.069	797.709	-53.639	0.043
	(0.044)	(0.096)	(18.046)	(477.210)	(186.538)	(0.032)
Controls						
Age	Y	Y	Y	Y	Y	Y
Gender	Y	Y	Y	Y	Y	Y
Length of Job Search at Baseline	Y	Y	Y	Y	Y	Y
Mean Dep Variable Control Group	8.436	8.747	146	3996	2,270	0.103
Std Dev Control Group	0.486	0.567	202	3,383	2,099	0.304
Observations	977	1,078	1,060	1,078	1,072	845
Adjusted R squared	0.046	0.033	0.015	0.032	0.039	0.01

they could pursue.

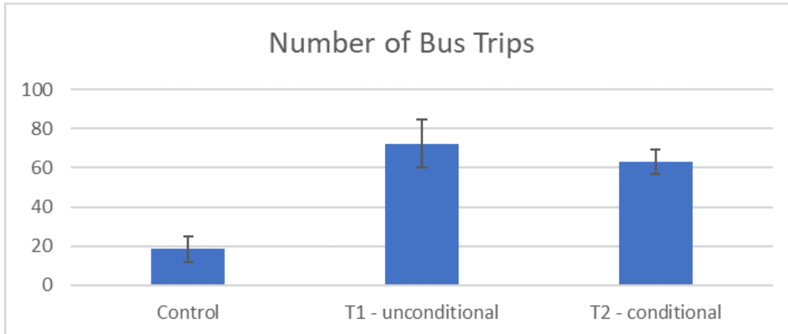

Figure 15: Number of Main Bus Line Trips based on Administrative Transport Data

Administrative Transport Data

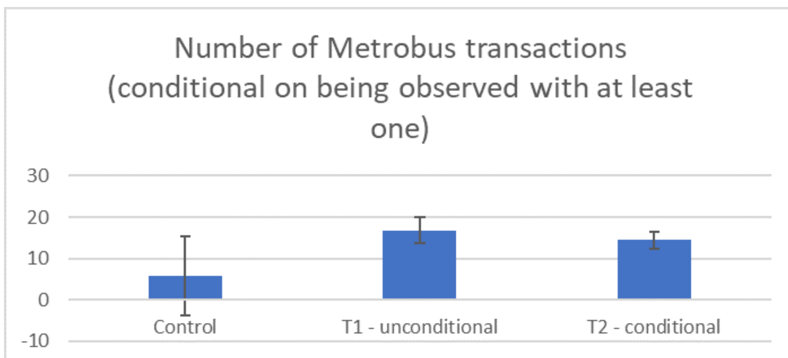

Figure 16: Number of Secondary Bus Line Trips based on Administrative Data

Administrative Transport Data

Reassuringly, Table 5 shows that those who say at baseline that they want to engage in job search strategies that require transport such as visiting job centers, travelling to firms and dropping off CVs (Panel B) are the ones who update the most. The interaction effect corresponds to a 3-percentage point reduction in the expected salary over the control mean.

We then examine whether job seekers who travelled the most are also the ones who are more likely to choose a job in their own township. Table 8 provides evidence that this is indeed the case. Using a quantile estimator, we find that restricting our sample to those who have a job at endline, the job seekers who were at the 75th percentile of the distribution of the number of trips taken during the intervention period (instrumented by the assignment to treatment) are much more likely

Table 5: Beliefs at the Baseline and Updating: ITT Results

Dependent Variable	**Log Reservation Wages**	**Log Expected Wage**	**Nbr Days needed to find another job**	**Salary Bias**	**Present Bias**
	(1)	(2)	(3)	(4)	(5)
Panel A:					
Treatment	-0.075*	0.005	38.005*	-52.242	9.946
	(0.039)	(0.042)	(20.925)	(224.858)	(194.238)
Treatment * Transp Strategy	-0.011	-0.153*	-11.219	-744.368*	776.539***
	(0.059)	(0.075)	(38.758)	(393.597)	(209.541)
Transp Strategy in Job Search	-0.076*	-0.065	27.722	-689.243*	-374.597***
	(0.043)	(0.072)	(24.618)	(357.000)	(96.126)
Panel B:					
Treatment	-0.033	-0.004	7.105	-97.468	251.314
	(0.049)	(0.040)	(22.752)	(269.826)	(193.133)
Treatment * CV Drop	-0.156*	-0.230***	39.050	-1,137.207**	517.678*
	(0.085)	(0.081)	(31.353)	(505.926)	(299.226)
CV Drop	0.032	-0.038	-17.258	-521.104	-340.244
	(0.071)	(0.062)	(18.618)	(393.234)	(204.005)
Controls					
Age	Y	Y	Y	Y	Y
Gender	Y	Y	Y	Y	Y
Length of Job Search at Baseline	Y	Y	Y	Y	Y
Mean Dep Variable Control Group	8.436	8.747	146	3996	2270
Std Dev Control Group	0.486	0.567	202	3383	2099
Observations	977	1078	1060	1,078	1,072
Adjusted R squared	0.043	0.045	0.008	0.048	0.044

to have chosen to stay in their own township.

Table 6: Instrumental Variable Quantile Estimation of Probability of Township Job Given Intensity of Search

Dependent Variable	**Has a Job in the Township (residualised)**		
	Quantile		
	25	**50**	**75**
Log Total Number of Trips	0.007	0.013	0.024***
	(0.041)	(0.028)	(0.007)
Observations	442	442	442

Note: Estimates from an instrumental variable quantile function as defined by Chernozhukov and Hansen (2008) and Machado and Santos Silva (2018). We instrument the Log Total Number of Trips with the indicator for assignment to treatment and the dependent variable is residualized from the variables age, gender, length of job search at baseline and date of recruitment into the sample. Source: Survey and Administrative Transport Data.

An additional concern is that the treatment may have induced job seekers to engage in more unproductive search activities such as dropping their CVs unsolicited, crowding out other potentially more effective forms of searching for jobs such as asking for referrals or submitting CVs online. To test this hypothesis, we create an indicator of high frequency of online application submissions, which equals 1 if the job seeker reports to submit CVs online once a week or more frequently. The indicator equals 0 if the job seeker submits CVs less than once a week. Figure 17 shows that there is no significant difference on online submissions between treatment and control groups, which suggests that the more extensive travel induced by the subsidy did not crowd out other potentially effective job search strategies.

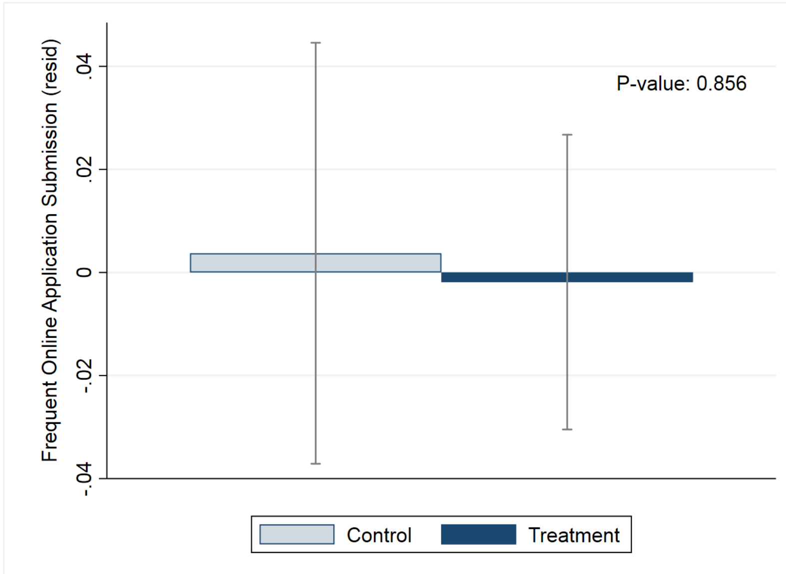

Figure 17: Frequency of Online Application Submission at Endline by Treatment Status

Figure 18 shows that there are no statistical differences between both groups in the frequency with which they request referrals from friends and relatives. If anything, the treatment group is more likely to invest in this search strategy.

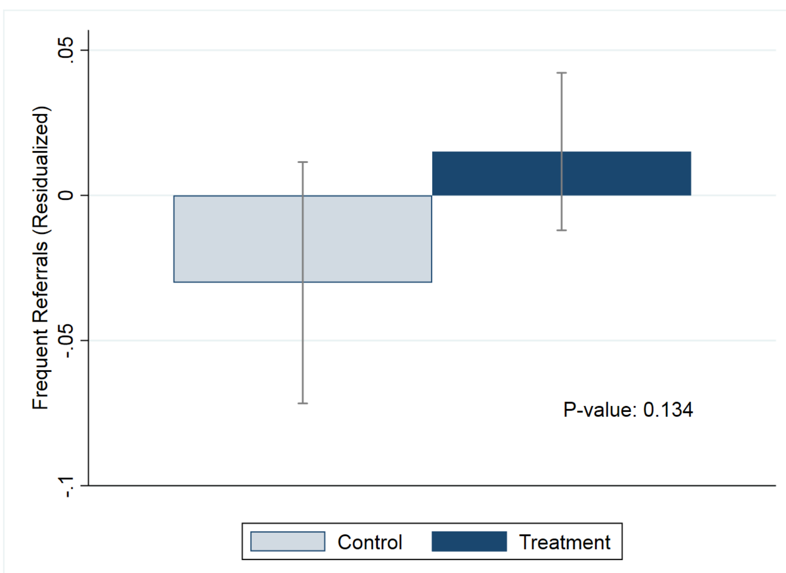

Figure 18: Frequency of Request for Referrals by treatment group at endline

Finally, 19 shows that those in the treatment group are not less likely to drop CVs for advertised vacancies and are marginally more likely to drop CVs for non-advertised positions.

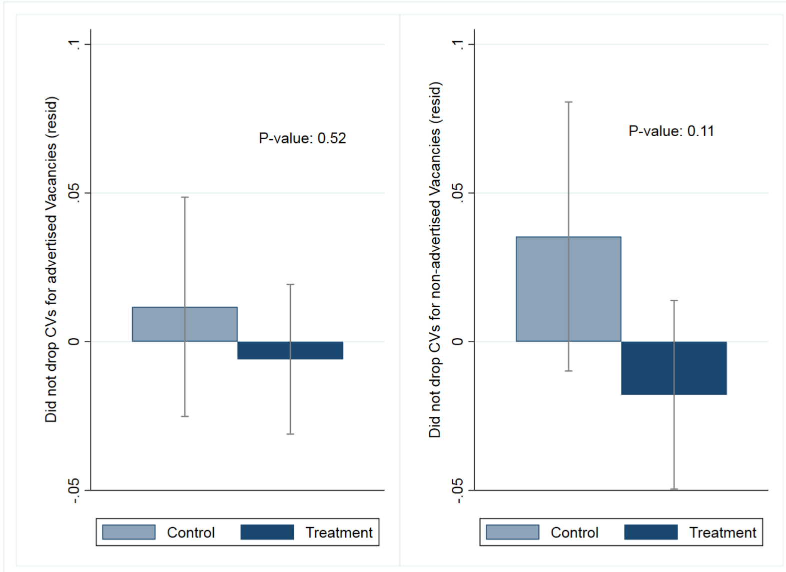

Figure 19: Share of job seekers who did not drop CVs by treatment status

These findings are therefore consistent with job seekers in the treatment group being no less active overall in the job search, despite spending more time travelling. This suggests that the subsidy did not induce sufficient compositional changes in job search activities between treatment and control groups to explain our findings. Note that once participants were enrolled in the study, all groups including the control group, were provided with general 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 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. Our informational intervention was very light-touch, as we provided no information on actual salaries for different occupations. As such, our findings should be interpreted as being close to how job seekers would have naturally searched for jobs and learned from this experience.

To confirm that the mechanism is exposure to the labor market and learning, we plot the correlation between job seekers in each experimental group who adjusted their salary expectations the most (defined as above the mean of the distribution in our sample) against the probability of accepting a job in the township, residualized from all the baseline covariates (age, gender, length of the job search and date of recruitment into the study). Reassuringly, figure 20 shows that job seekers who adjusted the most in the treatment group are significantly more likely to accept a job in the township.

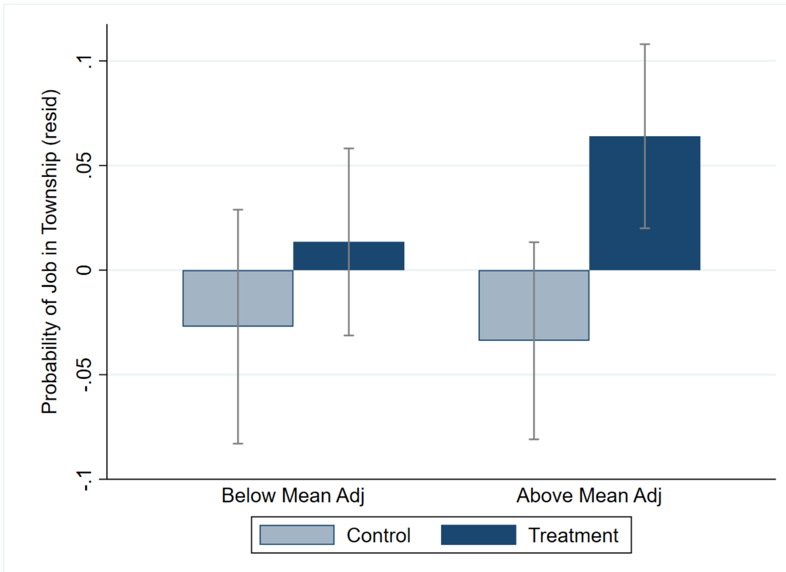

Figure 20: Probability of accepting a job in the township by the level of adjustment of salary expectations

Note: Values residualized from the following variables: age, gender, date of recruitment into the sample and the length of the job search at baseline. Source: Survey Data

4.2 Learning about commuting costs

In Figure 21 monthly earnings are residualized from potential predictors of wages such as gender, age and length of job search at baseline.

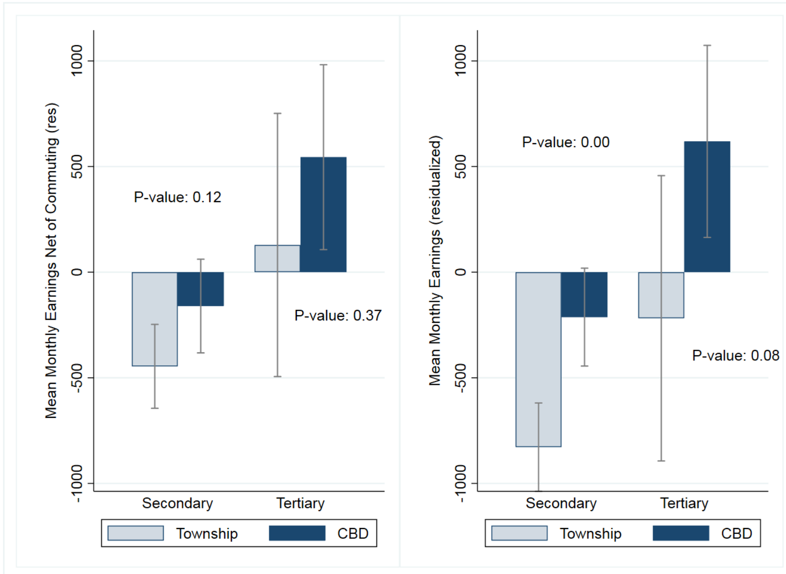

Figure 21: Monthly Earnings in the Township and in CBD (residualized)

These figures would be even more striking if we were to consider the opportunity cost of commuting. We conduct an additional exercise to try to assess whether job seekers are learning about commuting. While we cannot measure the disutility of commuting directly, we follow a revealed preference approach to observe commuting choices for those who hold jobs at the time we survey them at endline. We begin by restricting our analysis of the transport data to the period around the endline and to the sample of respondents who report being employed at that time. We further restrict the sample to only include trips that occurred between 4-9 am and 5-7 pm, Monday to Friday. This strategy brings us as close as possible to identifying commuting times for those that we can safely assume to be employed when we observe them in the transport administrative data.

Figure 24 suggests that the treatment group engaged in longer travel times on average during the job search (up to the quarter prior to the endline). By the endline, when we know for sure that the respondent is employed, we observe that commuting times were substantially lower in the treatment group relative to the control group. This is the case, both for commuting to jobs in the township and to jobs in the CBD. [8] This effect is more pronounced for those who accepted jobs in the CBD, consistent with the possibility that the disutility of commuting is significantly higher for

[8]Patterns are robust to different measurements of commuting times that do not restrict time or day of travel, or that identify commuting time as the modal travel time per month, suggesting that the smartcards might have been used primarily for the job search and for commuting.

the commute to the CBD.

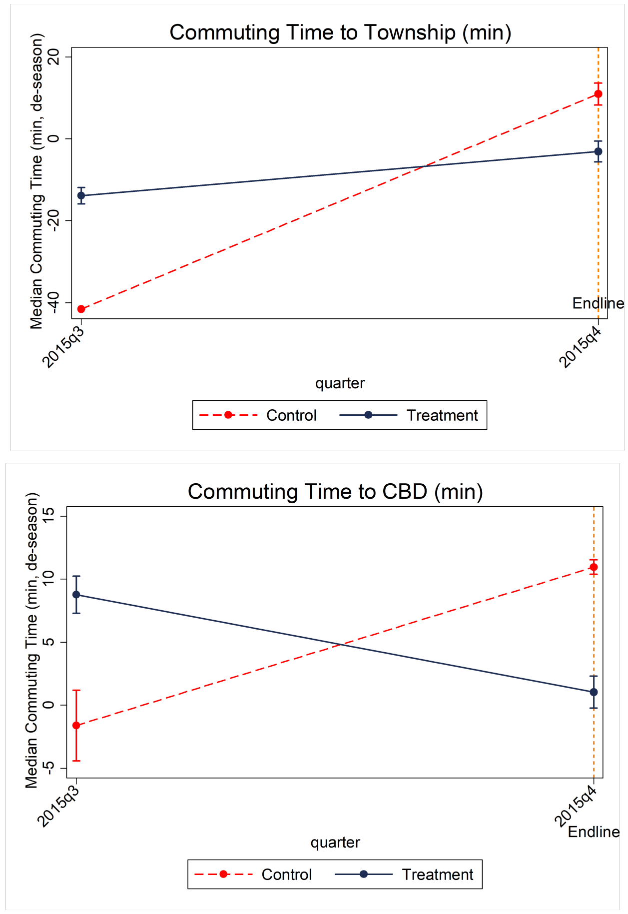

Figure 22: Travel and Commuting Time in Minutes to Jobs in CBD in the Township

Source: Administrative Transport Data

5 Balance Across Treatments

This section reports balance between treatment and control groups in our experimental design, across job seeker characteristics, employment histories and beliefs and expectations.

Table 7: Balance on Job Seeker Characteristics

	Control	T1 - unconditional	T2 - conditional	Overall	P-value of Test of Equality of Means: (1) vs. (2)	(1) vs. (3)	(2) vs. (3)	Joint Orthogonality
Job Seeker Characteristics								
Age of Job Seeker	25.000	25.189	25.091	25.093	0.417	0.716	0.707	0.717
	(0.161)	(0.170)	(0.191)	(0.102)				
Gender of Job Seeker	0.545	0.444	0.440	0.477	0.005	0.010	0.931	0.006
	(0.027)	(0.028)	(0.025)	(0.016)				
Completed Secondary Education	0.838	0.800	0.844	0.827	0.293	0.858	0.251	0.477
	(0.020)	(0.026)	(0.025)	(0.013)				
Attended or completed tertiary education	0.282	0.249	0.290	0.274	0.329	0.821	0.269	0.489
	(0.023)	(0.025)	(0.026)	(0.016)				
Lives alone	0.115	0.110	0.131	0.118	0.808	0.438	0.336	0.576
	(0.015)	(0.016)	(0.015)	(0.009)				
Number of household members	3.808	4.142	4.026	3.992	0.051	0.193	0.441	0.143
	(0.117)	(0.134)	(0.095)	(0.072)				
Number of adults in the household	2.493	2.642	2.690	2.607	0.321	0.176	0.780	0.329
	(0.097)	(0.110)	(0.126)	(0.067)				
Number of adult household members (18-65)	2.904	3.041	3.017	2.987	0.249	0.183	0.827	0.337
	(0.072)	(0.098)	(0.061)	(0.051)				
Share of employed members among all HH adults	0.274	0.250	0.272	0.265	0.224	0.901	0.211	0.362
	(0.013)	(0.013)	(0.013)	(0.008)				
Share of employed members among HH adults aged 18-65	0.283	0.259	0.277	0.273	0.272	0.753	0.347	0.497
	(0.014)	(0.014)	(0.014)	(0.008)				
Lives with at least one employed adult	0.647	0.625	0.670	0.647	0.599	0.515	0.187	0.391
	(0.026)	(0.031)	(0.025)	(0.018)				
Household members mean age	30.409	29.640	29.877	29.976	0.174	0.442	0.686	0.393
	(0.399)	(0.405)	(0.521)	(0.270)				
In the last month, total of incomes	1425.184	1240.255	1286.645	1317.730	0.177	0.216	0.715	0.320
	(92.281)	(92.630)	(70.177)	(45.762)				
How well can you use the following computer programs - Word	2.507	2.526	2.591	2.541	0.803	0.228	0.435	0.470
	(0.049)	(0.068)	(0.058)	(0.039)				
How well can you use the following computer programs - Excel	2.403	2.389	2.392	2.395	0.872	0.894	0.974	0.984
	(0.055)	(0.073)	(0.059)	(0.039)				
How well can you use the following computer programs - Powerpoint	2.249	2.326	2.315	2.297	0.383	0.358	0.907	0.549
	(0.056)	(0.067)	(0.059)	(0.036)				
Do you participate in any form of lottery or gambling?	0.165	0.157	0.151	0.157	0.742	0.605	0.852	0.855
	(0.016)	(0.022)	(0.021)	(0.011)				
Would you prefer R100 today or R200 in a month's time?	1.625	1.619	1.631	1.625	0.871	0.867	0.739	0.945
	(0.023)	(0.024)	(0.025)	(0.014)				
Level of risk aversion	1.871	1.866	1.884	1.873	0.819	0.577	0.488	0.761
	(0.016)	(0.020)	(0.014)	(0.009)				
Does anyone in your household receive any type of government grant?	0.515	0.569	0.533	0.539	0.187	0.697	0.373	0.379
	(0.027)	(0.029)	(0.029)	(0.015)				
Observations	365	365	352	1082				

Table 8: Balance on Employment Histories

	Control	T1 - unconditional	T2 - conditional	Overall	P-value of Test of Equality of Means (1) vs. (2)	(1) vs. (3)	(2) vs. (3)	Joint Orthogonality
Employment History and the Job Search								
Have you done any work for an employer between Jan 2011-Jan 2014?	0.584	0.589	0.543	0.572	0.866	0.292	0.248	0.472
	(0.030)	(0.030)	(0.024)	(0.018)				
If so how many jobs have you had in this period?	1.512	1.409	1.455	1.459	0.174	0.484	0.517	0.390
	(0.069)	(0.057)	(0.052)	(0.042)				
How many jobs have you applied since January 2014?	16.156	11.575	16.151	14.609	0.070	0.999	0.157	0.124
	(1.805)	(1.477)	(2.679)	(1.074)				
Years since last job	0.577	0.588	0.536	0.567	0.918	0.705	0.610	0.871
	(0.068)	(0.067)	(0.077)	(0.039)				
Looking for a government post	0.364	0.437	0.453	0.418	0.050	0.005	0.670	0.012
	(0.021)	(0.027)	(0.027)	(0.015)				
Looking for a job in retail	0.186	0.209	0.185	0.194	0.433	0.964	0.368	0.631
	(0.021)	(0.019)	(0.019)	(0.012)				
Looking for a job in manufacturing	0.101	0.093	0.097	0.097	0.745	0.842	0.905	0.941
	(0.015)	(0.020)	(0.017)	(0.010)				
Looking for a job in construction	0.071	0.077	0.054	0.068	0.795	0.338	0.216	0.371
	(0.013)	(0.015)	(0.012)	(0.008)				
Looking for a job in restaurant/hospitality	0.033	0.055	0.034	0.041	0.188	0.927	0.228	0.373
	(0.008)	(0.014)	(0.011)	(0.007)				
Looking for a job in business services	0.447	0.448	0.419	0.438	0.977	0.493	0.417	0.654
	(0.030)	(0.027)	(0.026)	(0.015)				
How long have you been actively looking for a job? Months	14.718	14.551	16.849	15.355	0.861	0.118	0.081	0.197
	(0.707)	(0.777)	(1.209)	(0.633)				
Have you had a job interview in the last 36 months?	0.532	0.485	0.510	0.509	0.320	0.626	0.586	0.607
	(0.039)	(0.037)	(0.030)	(0.024)				
What is the main strategy you use in trying to find a job?	2.600	2.381	2.392	2.458	0.083	0.164	0.933	0.188
	(0.093)	(0.095)	(0.094)	(0.053)				
Total of job search related expenses in last month	588.038	437.438	373.378	467.401	0.453	0.264	0.228	0.243
	(193.042)	(43.284)	(23.346)	(67.933)				
Total of general expenses in last month	1430.611	1393.888	1352.531	1392.822	0.823	0.604	0.767	0.867
	(125.449)	(117.455)	(65.779)	(60.860)				
Exposure to labour market - had jobs or had been to an interview	0.751	0.756	0.730	0.746	0.839	0.569	0.390	0.688
	(0.029)	(0.023)	(0.019)	(0.016)				
Observations	365	365	352	1082				

Table 9: Balance on Beliefs and Expectations

	Control	T1 - unconditional	T2 - conditional	Overall	P-value of Test of Equality of Means (1) vs. (2)	(1) vs. (3)	(2) vs. (3)	Joint Orthogonality
Employment History and the Job Search								
Have you done any work for an employer between Jan 2011-Jan 2014?	0.584	0.589	0.543	0.572	0.866	0.292	0.248	0.472
	(0.030)	(0.030)	(0.024)	(0.018)				
If so how many jobs have you had in this period?	1.512	1.409	1.455	1.459	0.174	0.484	0.517	0.390
	(0.069)	(0.057)	(0.052)	(0.042)				
How many jobs have you applied since January 2014?	16.156	11.575	16.151	14.609	0.070	0.999	0.157	0.124
	(1.805)	(1.477)	(2.679)	(1.074)				
Years since last job	0.577	0.588	0.536	0.567	0.918	0.705	0.610	0.871
	(0.068)	(0.067)	(0.077)	(0.039)				
Looking for a government post	0.364	0.437	0.453	0.418	0.050	0.005	0.670	0.012
	(0.021)	(0.027)	(0.027)	(0.015)				
Looking for a job in retail	0.186	0.209	0.185	0.194	0.433	0.964	0.368	0.631
	(0.021)	(0.019)	(0.019)	(0.012)				
Looking for a job in manufacturing	0.101	0.093	0.097	0.097	0.745	0.842	0.905	0.941
	(0.015)	(0.020)	(0.017)	(0.010)				
Looking for a job in construction	0.071	0.077	0.054	0.068	0.795	0.338	0.216	0.371
	(0.013)	(0.015)	(0.012)	(0.008)				
Looking for a job in restaurant/hospitality	0.033	0.055	0.034	0.041	0.188	0.927	0.228	0.373
	(0.008)	(0.014)	(0.011)	(0.007)				
Looking for a job in business services	0.447	0.448	0.419	0.438	0.977	0.493	0.417	0.654
	(0.030)	(0.027)	(0.026)	(0.015)				
How long have you been actively looking for a job? Months	14.718	14.551	16.849	15.355	0.861	0.118	0.081	0.197
	(0.707)	(0.777)	(1.209)	(0.633)				
Have you had a job interview in the last 36 months?	0.532	0.485	0.510	0.509	0.320	0.626	0.586	0.607
	(0.039)	(0.037)	(0.030)	(0.024)				
What is the main strategy you use in trying to find a job?	2.600	2.381	2.392	2.458	0.083	0.164	0.933	0.188
	(0.093)	(0.095)	(0.094)	(0.053)				
Total of job search related expenses in last month	588.038	437.438	373.378	467.401	0.453	0.264	0.228	0.243
	(193.042)	(43.284)	(23.346)	(67.933)				
Total of general expenses in last month	1430.611	1393.888	1352.531	1392.822	0.823	0.604	0.767	0.867
	(125.449)	(117.455)	(65.779)	(60.860)				
Exposure to labour market - had jobs or had been to an interview	0.751	0.756	0.730	0.746	0.839	0.569	0.390	0.688
	(0.029)	(0.023)	(0.019)	(0.016)				
Observations	365	365	352	1082				

6 Attrition

In this section we show that attrition was relatively small and unbiased across treatment and control groups during our experiment. Column 1 shows the p-value for a test of equality of means, assuming unequal distributions, while column 2 shows the p-value for a kolmogorov smirnov non-parametric test for the equality of distributions.

Table 10: Balance Between Baseline and Endline Samples

	P-value equality of means	**P-value equality of distributions**
What is your age?	0.3187	0.251
What gender do you identify with?	0.0033	0.028
Lives alone	0.7854	1.000
Number of household members	0.4142	0.996
Number of adult household members (over 18)	0.2974	0.815
Number of adult household members (18-65)	0.2418	0.854
Share of employed members among all HH adults	0.9361	0.915
Share of employed members among HH adults aged 18-65	0.9375	1.000
Lives with at least one employed adult	0.7859	1.000
Household members mean age	0.3805	0.382
Have you done any work for an employer between Jan 2011-Jan 2014?	0.3272	0.975
If so How many jobs have you had in this period?	0.2188	0.919
In the last month, total of incomes	0.7098	0.356
How many jobs have you applied since January 2014?	0.7396	0.596
Looking for a government post	0.1532	0.728
Looking for a job in retail	0.3925	1.000
Looking for a job in manufacturing	0.8569	1.000
Looking for a job in construction	0.7396	1.000
Looking for a job in restaurant/hospitality	0.0957	0.984
Looking for a job in business services	0.6918	1.000
Looking for any work	0.1166	0.610
How long have you been actively looking for a job? (Months)	0.6314	0.180
What is the main strategy you use most frequently in trying to find a job?	0.668	0.825
Average salary expected - all categories	0.4463	0.889
Years since last interview	0.244	0.932
Total of job search related expenses in last month	0.7823	0.336
Total of general expenses in last month	0.8405	0.399
What do you think is the likelihood that you will find a job in the next year?	0.8104	1.000
What do you think is the likelihood you'll find a job in the next 2 months?	0.902	1.000
Exposure to labour market - had jobs or had been to an interview	0.8419	1.000
Are you a member of a community - Church/ Youth group	0.2639	0.913
Which community helped you in job search- Church/ Youth group	0.7841	1.000
Where on the ladder do you feel you stand at the moment (financial situation)?	0.8036	1.000
Which step do you think you will be on in 5 years time (financial situation)?	0.6742	0.880
Where on the ladder do you feel you stand at the moment (health and happiness)?	0.3235	0.500
Which step do you think you will be on in 5 years time (health and happiness)?	0.9994	1.000
How well can you use the following computer programs - Word	0.719	0.999
How well can you use the following computer programs - Excel	0.5804	0.907
How well can you use the following computer programs - Powerpoint	0.3196	0.497
Do you participate in any form of lottery or gambling?	0.7405	1.000
Would you prefer R100 today or R200 in a month's time?	0.1759	0.813
Risk aversion question	0.1649	0.942
Do you participate in any form of lottery or gambling?	0.7405	1.000
Does anyone in your household receive any type of government grant?	0.10	0.482

7 Stability of the Results over the Covariate Space

In this section, we check whether the treatment effects are relatively stable across the covariate space, for all the covariates in the baseline specification including the date of recruitment into the sample, the age, gender and the length of the job search at baseline. Figures 23 through 26 are histograms of the pointwise derivatives describing the marginal effect of covariates at each datapoint. These result from the implementation of a Kernel-based regularized least squares (krls), which is a machine learning method to fit multidimensional functions for regression (Hainmueller and Hazlett, 2013). In all cases, pointwise derivatives are normally distributed suggesting that the treatment effects are fairly stable across the covariate space.

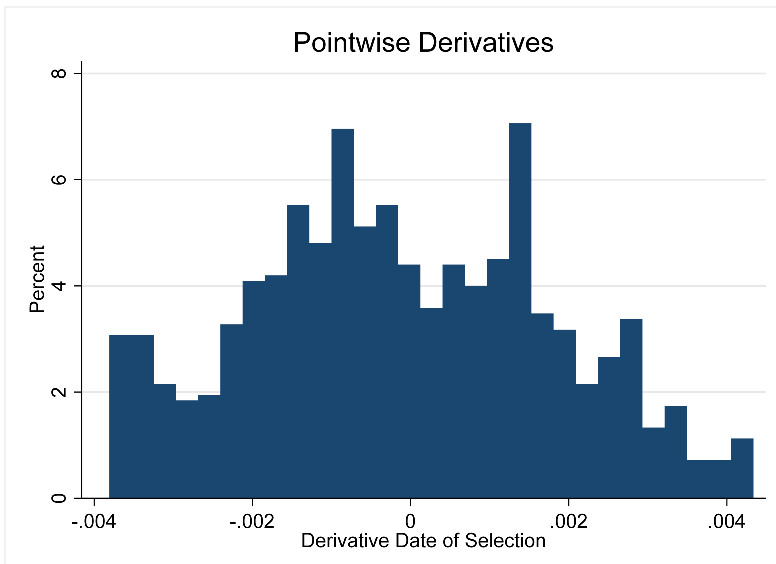

Figure 23: Histogram of Pointwise Derivations for Date of Selection into Treatment

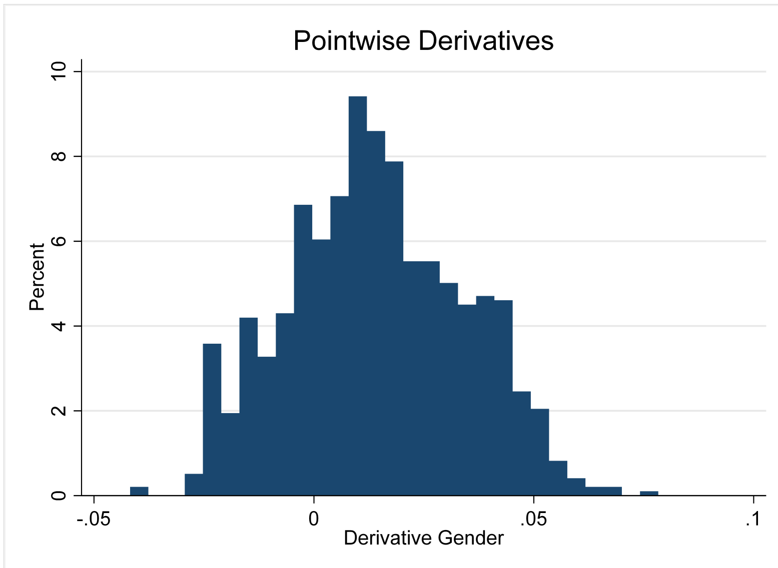

Figure 24: Histogram of Pointwise Derivations for Gender

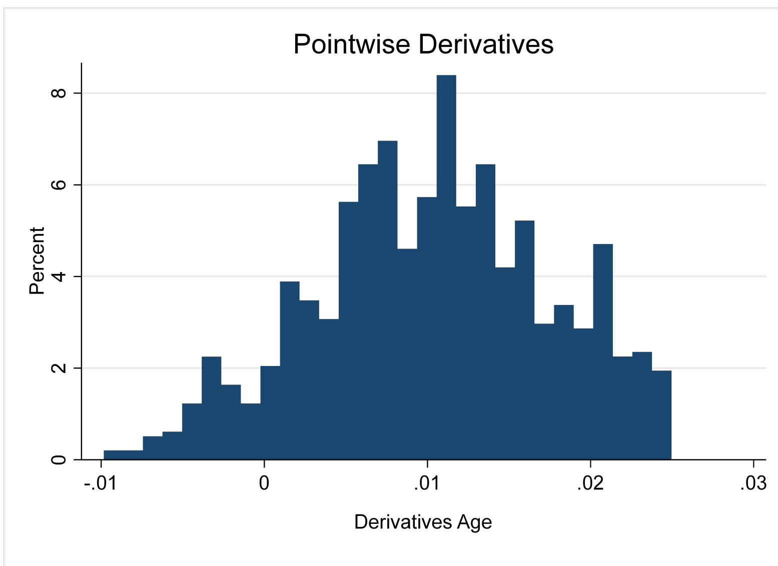

Figure 25: Histogram of Pointwise Derivations for Age

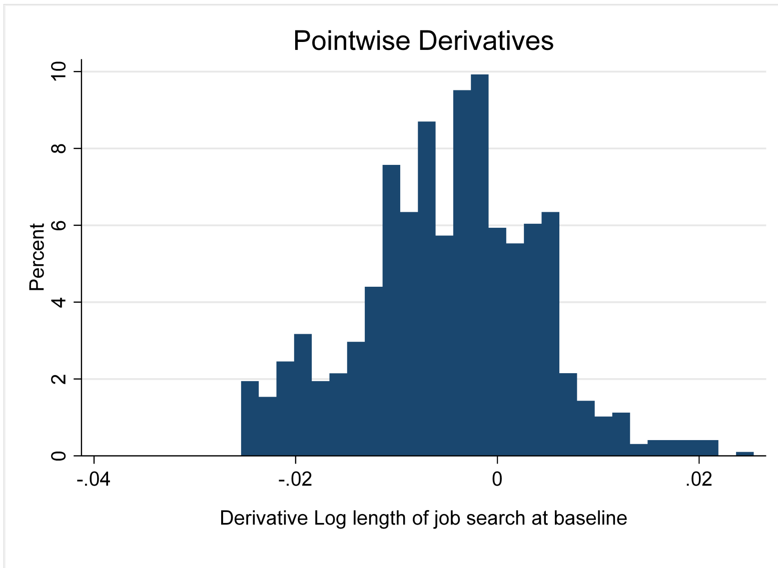

Figure 26: Histogram of Pointwise Derivations for Job Search at Baseline

8 Non-compliance and Treatment on the Treated

Take up of our job search subsidies was high with 84% of the sample using the transport smartcards at some point between baseline and endline. The remaining 16% failed to use the card because there was either no bus stop close to their homes or because the card was lost. In Table 11, we show the treatment on the treated effects correcting for non-compliance. Our first stage prediction of actual take up using the original assignment to treatment is sizable and significant, and well above the conventional levels for a strong instrument, with a Kleibergen-Paap F statistic of above 30. The magnitude of the treatment on the treated effects is then considerably larger than the ITT estimates -by a factor of almost 6 for reservation wages, suggesting significant attenuation bias due to non-compliance.

Table 11: Treatment on the Treated: Effects on Beliefs and Expectations

Dependent Variable	**Log Reservation Wages**	**Log Expected Wage**	**Nbr Days needed to find another job**	**Salary Bias**	**Present Bias**
	Panel A: 2SLS Estimates				
Treatment	-0.498**	-0.305**	186.074**	-1,857.938**	2,070.593**
	(0.208)	(0.129)	(87.703)	(855.239)	(1,046.330)
	Panel B: First-Stage Estimates				
	Dep. Variable: Job Seeker Reports using Card				
Assignment to Treatment	0.155***	0.166***	0.168***	0.166***	0.163***
	(0.025)	(0.024)	(0.025)	(0.024)	(0.023)
Controls					
Age	Y	Y	Y	Y	Y
Gender	Y	Y	Y	Y	Y
Length of Job Search at Baseline	Y	Y	Y	Y	Y
Kleibergen-Paap F stat	31.323	39.963	39.167	39.963	38.828
Mean Dep Variable Control Group	8.436	8.747	146	3452	2267
Std Dev Control Group	0.486	0.567	202	3411	2099
Observations	976	1,077	1,059	1,077	1,072

In Table 12, we present the treatment on the treated effects for the job search outcomes.

Table 12: Treatment on the Treated: Effects on Beliefs and Expectations

Dependent Variable	**Log Number Applications to Jobs**	**Log Number of Interviews**	**Conversion App. to Interviews**	**Conversion Interviews to Jobs**	**Log Job Offers**
			Panel A: 2SLS Estimates		
Treatment	0.096	0.373	-0.196	-0.071	0.080
	(0.566)	(0.332)	(0.181)	(0.117)	(0.216)
			Panel B: First-Stage Estimates		
			Dep. Variable: Job Seeker Reports using Card		
Assignment to Treatment	0.149***	0.161***	0.154***	0.154***	0.184***
	(0.027)	(0.026)	(0.028)	(0.028)	(0.026)
Controls					
Age	Y	Y	Y	Y	Y
Gender	Y	Y	Y	Y	Y
Length of Job Search at Baseline	Y	Y	Y	Y	Y
Kleibergen-Paap F stat	31.634	43.743	29.809	29.809	51.131
Mean Dep Variable Control Group	2.268	0.704	0.205	0.186	0.438
Std Dev Control Group	1.140	0.687	0.412	0.299	0.508
Observations	936	946	898	898	579

In table 13 we show that the sample of job seekers who reported using the smartcard during our intervention is balanced on important covariates across treatment and control groups.

Table 14 further shows that non-compliance is uncorrelated with specific job seeker level characteristics such as age, gender, history of job search, but that it is strongly predicted by the treatment.

Table 13: Balance across treatment and control: Sample that used Smartcards

					P-value of Test of Equality of Means			
Sample Restricted to Job Seekers who used the Smartcard	**Control**	**Uncond**	**Cond**	**Overall**	**(1) vs. (2)**	**(1) vs. (3)**	**(2) vs. (3)**	**Joint Orthogonality**
Age	25.026	25.252	25.028	25.107	0.354	0.995	0.455	0.568
	(0.191)	(0.146)	(0.262)	(0.118)				
Gender	0.560	0.464	0.440	0.484	0.064	0.018	0.390	0.044
	(0.045)	(0.020)	(0.019)	(0.019)				
Has completed secondary education	0.842	0.788	0.854	0.827	0.097	0.772	0.112	0.129
	(0.025)	(0.020)	(0.035)	(0.017)				
Attended or completed tertiary education	0.297	0.265	0.285	0.281	0.419	0.795	0.626	0.693
	(0.032)	(0.024)	(0.034)	(0.017)				
Number of household members	3.759	4.196	4.016	4.004	0.039	0.142	0.400	0.079
	(0.103)	(0.164)	(0.137)	(0.084)				
Number of adult household members (18-65)	2.891	3.047	3.000	2.984	0.282	0.223	0.730	0.372
	(0.065)	(0.124)	(0.055)	(0.050)				
Share of employed members among HH adults (18-65)	0.284	0.259	0.277	0.273	0.223	0.765	0.367	0.397
	(0.017)	(0.013)	(0.014)	(0.009)				
Have you done any work for an employer in the last 3 years?	0.609	0.598	0.541	0.581	0.810	0.141	0.159	0.220
	(0.036)	(0.026)	(0.030)	(0.018)				
If so how many jobs have you had in this period?	1.500	1.422	1.480	1.465	0.472	0.856	0.539	0.713
	(0.090)	(0.063)	(0.070)	(0.042)				
In the last month, total of incomes	1461.361	1283.754	1321.611	1349.320	0.247	0.288	0.753	0.456
	(112.800)	(103.167)	(60.640)	(51.957)				
How long have you been actively looking for a job? Months	13.868	13.885	17.123	15.013	0.992	0.026	0.041	0.033
	(1.062)	(1.199)	(0.938)	(0.701)				
Total of job search related expenses in last month	686.545	437.826	391.190	494.772	0.370	0.282	0.557	0.476
	(268.706)	(71.298)	(35.363)	(83.603)				
Total of general expenses in last month	1382.113	1317.517	1373.209	1356.034	0.622	0.941	0.688	0.874
	(84.734)	(104.067)	(92.619)	(55.790)				
Have you had a job interview in the last 36 months?	0.538	0.467	0.517	0.506	0.375	0.736	0.372	0.609
	(0.060)	(0.052)	(0.021)	(0.027)				
What do you think is the likelihood that you will find a job in the next year?	3.415	3.339	3.377	3.375	0.243	0.569	0.559	0.492
	(0.046)	(0.045)	(0.048)	(0.027)				
What do you think is the likelihood you'll find a job in the next 2 months?	2.764	2.606	2.672	2.676	0.074	0.176	0.356	0.175
	(0.060)	(0.066)	(0.025)	(0.032)				
Exposure to labour market - had jobs or had been to an interview	0.763	0.754	0.734	0.750	0.862	0.493	0.644	0.741
	(0.039)	(0.033)	(0.026)	(0.019)				
How well can you use the following computer programs - Word	2.575	2.564	2.604	2.581	0.902	0.771	0.564	0.841
	(0.082)	(0.042)	(0.057)	(0.034)				
How well can you use the following computer programs - Excel	2.466	2.439	2.405	2.435	0.764	0.531	0.682	0.810
	(0.072)	(0.057)	(0.061)	(0.035)				
How well can you use the following computer programs - Powerpoint	2.305	2.383	2.323	2.339	0.321	0.826	0.395	0.527
	(0.064)	(0.052)	(0.048)	(0.031)				
Would you prefer R100 today or R200 in a month's time?	1.617	1.607	1.630	1.618	0.820	0.750	0.515	0.802
	(0.034)	(0.022)	(0.026)	(0.016)				
Does anyone in your household receive any type of government grant?	0.509	0.578	0.517	0.537	0.133	0.849	0.153	0.232
	(0.031)	(0.030)	(0.030)	(0.018)				
Observations	321	316	903					

Table 14: Balance on Job Seeker Characteristics

Dependent Variable	**Job Seeker Used Smartcard**
Age	0.001
	(0.003)
Gender	0.023
	(0.029)
Length of Job Search at Baseline	-0.018
	(0.013)
Date of Recruitment	-0.002
	(0.002)
Mean Dep Variable Control Group	0.729
Std Dev Control Group	(0.445)
Observations	1081
Adjusted R Squared	0.048