Evidence on Job Search Models from a Survey of Unemployed Workers in Germany*

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Abstract

The job finding rate of Unemployment Insurance (UI) recipients declines in the initial months of unemployment and then exhibits a spike at the benefit exhaustion point. A range of theoretical explanations have been proposed, but those are hard to disentangle using data on job finding alone. To better understand the underlying mechanisms, we conducted a large text-message-based survey of unemployed workers in Germany. We surveyed 6,800 UI recipients twice a week for 4 months about their job search effort. The panel structure allows us to observe how search effort evolves within individual over the unemployment spell. We provide three key facts: 1) search effort is flat early on in the UI spell, 2) search effort exhibits an increase up to UI exhaustion and a decrease thereafter, 3) UI recipients do not appear to time job start dates to coincide with the UI exhaustion point. A model of reference-dependent job search can explain these facts well, while a standard search model with unobserved heterogeneity struggles to explain the second fact. The third fact also leaves little room for a model of storable offers to explain the spike.

JEL Codes: J64, J65, D91.

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1 Introduction

To tell apart different models of job search, the key piece of evidence is typically the path of the hazard rate from unemployment to employment. The evidence from administrative data sets suggests three common patterns, from the US (Ganong and Noel, 2019) to Spain (Domenech and Vannutelli, 2019), from France (Marinescu and Skandalis, 2019) to Slovenia (Boone and van Ours, 2012): (i) the hazard rate from unemployment typically declines in the initial months of unemployment; (ii) it increases near expiration; (iii) it declines again following expiration, creating a spike at UI exhaustion. We find those same patterns in Germany for recipients with potential unemployment duration ranging from 6 to 15 months (Figure 1a).[1]

As well-established as these patterns are, it is not obvious to translate them into job search models because of the role of unobserved heterogeneity and other confounders. Does the decline in job finding rate in the initial months reflect workers discouragement, or the fact that more able workers get jobs faster? Does the spike of the hazard rate at exhaustion reflect increase search intensity, or previous offers that the workers extended, as in the storable offer models (Boone and van Ours, 2012)? With aggregate hazard rates, one can attempt to separate the different models, but the ability to do so is ultimately limited by the fact that we do not observe the path of search effort within worker, only the aggregate composition. One would ideally like within-worker measure of search intensity over the spell.

In this paper, we provide evidence on search intensity from a panel survey of unemployed workers in Germany. In doing so, we build on the pioneering work of Krueger and Mueller (2011, KM) who surveyed a panel of unemployed workers in New Jersey in the wake of the Great Recession. As important as the lessons from KM are, they are limited in the ability to address the questions above by the repeated UI benefits extensions in their time frame.

We survey 6,877 unemployed workers in Germany for 18 weeks between November 2017 and November 2019. Throughout, the economic environment is stable, with the unemployment rate between 5% and 6%. To disentangle the survey responses from time or cohort effects, we stagger the start of interview over 20 months, and we randomize the time of contact during the spell, e.g., in months 2, 5, 8, 11, or 13. We contact groups with 5 different potential benefit durations (PBD): 6, 8, 10, 12, and 15 months. The variation in PBD of 6, 8, 10, or 12 months depends on the length of contributions to the UI system, while the difference between PBD of 12 or 15 months depends on an age discontinuity (as studied by Schmieder and Trenkle, 2020).

A novel design feature is that, instead of conducting a phone or web survey, we use SMS

[1] For a recent survey on the effects of UI on job finding rates see Schmieder and von Wachter (2016).

messages, a survey method used to some extent in developing countries (e.g. Ballivian et al. 2015; Hoogeveen et al. 2014; Berkouwer and Dean 2019) and epidemiological research (e.g. Kuntsche and Robert 2009; Johansen and Wedderkopp 2010) but a novelty, as far as we know, in our context. This survey feature was chosen to limit exhaustion and attrition. We contact 86,673 unemployed workers with a letter letting them known of the upcoming text message; a few days later we send text messages asking for consent to participate in a survey. Among the 7,797 respondents who consent, the 6,877 workers who report still being unemployed constitute our main sample. The respondents receive text messages twice a week, on Tuesday and Thursday, with a question on search effort (translated from German): "*How many hours did you spend searching for a job yesterday? For example, looking for job-postings, sending out applications or designing a cv. Please reply with the number of hours, e.g. "0.5", or "2". If, for whatever reason, you did not look for a job simply respond with "0"*".

Our measure of search intensity is the answer to this question for the individuals who report still being unemployed. Before we turn to our main findings, we document four encouraging features of this measure. First, the average number of minutes of job search, 81 minutes per day, is comparable to the average search intensity in the KM survey (70 minutes on weekdays) and in the Survey of Consumer Expectations supplement (77 minutes, Faberman et al., 2017), and somewhat higher than in the American Time Use Survey (48 minutes, Krueger and Mueller, 2010). Second, the measure of search effort displays no obvious time trend and only limited seasonality, making the use of time controls of limited importance. Third, it responds strongly to plausible determinants of search intensity: the measure declines by 75 percent upon receiving a job offer, and by 30 percent on a holiday.

The fourth validation is the most critical for our design, since it enables us to focus on within-person search intensity. Compare two groups of survey participants who are unemployed in month 5 of potential duration; the first group was randomized to receive the invitation to participate on month 2, while the second group on month 5. We would like the two groups to have similar reported search intensity, so that when the survey *started,* conditional on month of unemployment and current unemployment status, is not material to the response. This property could fail because, for example, individuals start off over-reporting the number of hours search but become more truthful as the survey goes on. We document that in our sample there is no systematic difference in average search effort between the two groups, that is, the between-worker and within-worker estimates are comparable. This is a different pattern than in the KM survey. While we cannot tell for sure, the SMS format, making response easy and not time-consuming, likely contributed to this pattern in our survey.

Having established these desirable properties, we turn to three key pieces of evidence from our survey. First, we provide evidence on the path of search effort in the initial months, far from exhaustion. The standard model predicts an increase, while other models predict a decrease, say due to discouragement or habituation. Second, we provide evidence on the path of search effort near exhaustion. The standard model predicts an increase up to exhaustion, with a constant effort thereafter. A reference-dependent model with backward-looking reference points (DellaVigna et al., 2017) also suggests an increase up to exhaustion, but a decrease thereafter. Third, we focus on the role of storable offers. Namely, we test whether individuals who report getting a job near benefit expiration seem to time the job start date to coincide with UI exhaustion. For each of these findings, we compare the results (as in DellaVigna and Pope, 2018 and DellaVigna et al. (2019)) to the average prediction of 35 experts on job search.

For the first finding, we consider the intensity of search effort from month 2 (as early as we could survey unemployed respondents) to month 6, excluding the group with 6-month PBD. On average, the experts expect a 20 percent decrease in search intensity over this period. Instead, the search intensity stays flat, from 87 minutes in month 2 to 88 minutes (s.e.=2.8 minutes) in month 6. This contrasts with a sharp decrease in the hazard rate from unemployment from 12 percent to 7 percent over the same unemployment length. This suggests that the decline in hazard rates is unlikely to be due to a discouragement effect.

For the second finding, we focus on search effort around the UI exhaustion. On average, the experts expect search effort to increase substantially in the months leading to UI exhaustion, as predicted by most models, other than a pure storable-offer model of the "spike"; interestingly, they also forecast a similar-sized decline in the 3 months past exhaustion, as predicted under reference dependence. We find evidence qualitatively consistent with this prediction: search effort increases by 7 minutes (s.e.: 2.0 minutes) up to expiration, and then decreases by 5.7 minutes (s.e.: 1.9 minutes). Thus the "spike" in hazard is matched by a similar "spike" in search intensity, even if, in percent terms, the increase in minutes searched is smaller.

The third finding concerns the storable-offer model. We compute the average number of days between the (reported) job offer and job start. The experts on average expect this offer-start gap to be 50 percent larger for individuals starting their job in the month of UI expiration, versus in other months. Instead, we find the gap to be about the same for the two groups, and no evidence of storable offers also using an alternative measure.

We then turn to whether a model of job search can quantitatively explain our findings on the path of search effort throughout the UI spell, as well as the observed reemployment hazard. We generate reemployment hazard rates using administrative data for a comparable population as the survey sample. Using both the search effort and hazard paths as target moments, we estimate via minimum distance a model with costly search effort and an optimal consumption choice. As far as we know, this is the first estimate of a job search model with information on both the inputs (the search intensity) and the outputs (the hazards).

Building on DellaVigna et al. (2017), we compare a standard job search model with unobserved heterogeneity with a reference-dependent model which allows for loss aversion with respect to recent income. In the reference-dependent model, unemployed individuals search especially hard when current consumption lags recent income, for example at UI expiration, as loss aversion makes unemployment especially painful; over time, however, they get habituated as the reference point adapts, and thus the search intensity declines.

Overall, the reference-dependent model fits significantly better. The difference is not due to the hazard moments, which the two models fit similarly well, but to the search effort moments near UI expiration. The reference-dependent model fits well the increase and then decrease of effort near expiration, with the decrease explained by the reference-point adaptation. The standard model, instead, fits well the increase but cannot explain the subsequent decrease. Perhaps surprisingly, both models fit quite well the flatness of the search effort in the initial months. Importantly, while the findings on storable offers are not used in the estimation, the models match closely the spike at UI expiration, consistent with the data providing little support for storable offers in the German context.

We consider informally other models and factors that could affect our conclusions. A model of worker discouragement (perhaps because of perceived skill depreciation as in Kroft et al., 2013) could generate a decrease in search effort post expiration, but it would not seem to explain the flat search profile in the initial months, when discouragement would seem most likely. A model with a fixed pool of jobs (as discussed in Faberman and Kudlyak, 2019) to search could generate a decrease in search effort post expiration, as workers sampled most available jobs by the deadline; however, this model would predict a dip in search effort after expiration, rather than the observed smooth decrease. Temporary layoffs of workers who are later recalled (as in Katz, 1986; Katz and Meyer, 1990) could explain the spike in hazards at expiration, but while such recalls appear important in other settings we show that they are relatively uncommon in Germany and do not affect the hazard rate.

The paper is related to other papers measuring search effort over the unemployment spell. As mentioned above, we build on the survey of unemployed workers in KM, but unlike in KM we are able to examine search effort at expiration. Two papers measure search effort with activity on online postings: Marinescu and Skandalis (2019) using data from activity on the web portal for unemployed workers in France documents a similar increase and decrease of search effort near expiration; Faberman and Kudlyak (2019) using activity on an online job search platform in the US cannot study search effort at expiration, but, like us, does not find evidence of a decrease in search effort in the initial months. We view the two forms of evidence as highly complementary. The survey-based measure is based on a self report, unlike the administrative measure in the job portals, but has the advantage that it covers all forms of job search, not just a specific, and infrequent, job search activity.[2]

The paper is also related to papers bringing to bear evidence on job search models (e.g. Card et al., 2007; Nekoei and Weber, 2017; Kolsrud et al., 2018; Belot et al., 2019; Ganong and Noel, 2019) and the disincentive effects of UI (Rothstein, 2011; Lalive et al., 2015; Johnston and Mas, 2018; Leung and O'Leary, 2019; Le Barbanchon et al., 2019). The evidence from within-person search effort complements the traditional information on hazard rates from unemployment. Indeed, in our context using just the hazard rates we would be unable to distinguish between models. Our finding of a flat within-person profile in search effort is consistent with evidence from Mueller et al. (2018) suggesting that the decline in hazard is more likely due to unobserved heterogeneity than true duration dependence. Our finding of a spike in search effort around UI expiration is consistent with the reference-dependent explanation of evidence from a reform in Hungary (DellaVigna et al., 2017), with comparable degrees of loss-aversion, though a longer adaptation period.

The paper is also related to evidence on reference dependence using field data (e.g. Sydnor, 2010; Barseghyan et al., 2013; Allen et al., 2017; Rees-Jones, 2018; O'Donoghue and Sprenger, 2018; Barberis, 2018). The paper provides additional evidence pointing in the direction of backward-looking, adaptive reference points (e.g. Thakral and Tô, forthcoming), for example because of memory (Bordalo et al., forthcoming).

Finally, methodologically our paper also highlights the potential benefits of using SMS messages to run surveys. Respondents in our sample participated twice a week for 4 months, with relatively low attrition, and at a moderate cost. The trade-off relative to more traditional methods—phone and online surveys—is that SMS-based survey lend themselves more to cases with few, simple questions and answers, like ours.

2 Survey Design and Setting

The target group for the survey are prime-age recipients of UI benefits in Germany. The German UI system has been studied extensively (e.g. Fitzenberger and Wilke, 2010; Schmieder et al., 2012; Caliendo et al., 2013; Dlugosz et al., 2014; Schmieder et al., 2016; Altmann et al., Forthcoming). The key features are that individuals who become unemployed and have

[2] Other related papers provide evidence on the intensity of search activities in response to various reforms, e.g., Lichter and Schiprowski (2020) and Arni and Schiprowski (2019).

worked at least 12 out of the 30 previous months are eligible to UI benefits at a replacement rate of 60 percent (67 percent for workers with children). UI claimants can receive benefits up to the potential benefit duration (PBD), which is determined by the prior work history. While on UI, unemployed workers regularly meet with caseworkers who provide support, monitor job search efforts, and may assign workers to active labor market programs (see Schmieder and Trenkle, 2020, for more details). After UI benefits are exhausted workers may claim a second tier of benefits called "Unemployment benefits 2" which is a means tested program on the household level and generally substantially less generous than regular UI benefits.

The survey was funded and conducted by the **Institute of Employment Research (IAB)**, the research institute of the German Federal Employment Agency.[3] Since the UI system is overseen by the Federal Employment Agency, the IAB has direct access to the administrative data on UI claims and the work history of the claimants. Conducting the survey closely integrated with the administrative data provides three crucial advantages: a) the administrative data allows for a very targeted sample (workers with specific benefit durations – potentially with quasi random variation such as age discontinuities; workers close to UI exhaustion; etc.) and easy checks for the representativeness of the sample, b) the administrative data provides extensive and precise background information that does not have to be obtained via a survey instrument (demographics, past labor market history, UI eligibility, ...) and c) participants can be followed even after the survey has concluded.

The first wave of UI recipients was contacted in November 2017 (see Figure 2a for an illustration of the timing). Through the IAB, we were able to obtain the universe of UI recipients in each month of our survey with about a 3 week delay, i.e. at the beginning of November 2017 we could obtain a snapshot of all UI recipients as of October 15th, 2017, together with information on mobile phone numbers, demographics and potential UI benefit durations. Among the UI claimants with recorded cellphone numbers (about 80% of all claimants), we selected a (stratified) random sample of UI recipients for whom we then obtained addresses from the administrative UI data. The contacted individuals first received a letter and a flyer in the mail (see Online Appendix Figure A.1 and A.2) explaining the format of the survey, the anonymity of the responses, and the incentives we offer for participation (20 euro in form of Amazon gift vouchers for participating for the full survey duration).[4] After receiving the

[3]The direct costs of conducting the survey was born by the IAB. Additional funding for researcher time and research assistance positions came from the Alfred P. Sloan Foundation, the German Science Foundation (DFG) and the US National Science Foundation (NSF).

[4]Once an individual consents, she receives a 5 Euro Amazon gift voucher (in form of a Code via SMS). If the individual keeps responding to questions, she receives another 5 Euro voucher after the first 2 months and a final 10 Euro voucher after completing the entire 18 weeks. About 60% of vouchers were redeemed as of December 2019, 2 months after the end of the survey (see Online Appendix Table A.1).

letter on a Thursday (approximately), the UI recipients are then contacted on the following Tuesday directly via SMS.[5] This initial SMS contact asks the UI recipients for their consent to participate in the survey and to allow us to link their responses to the administrative data. If the person consents to the survey, we then ask her the first question on job search effort. From then onwards for the next 18 weeks, we contact the participants each Tuesday and Thursday to ask about their job search activities.

The sample for this initial (and each subsequent) wave consisted of 2 distinct groups: a set of 'short-eligibility' workers, with potential benefit durations (PBD) of 6, 8 or 10 months, and a set of 'long-eligibility' workers, with either 12 or 15 months of PBD. The short-eligibility group consists of workers age 28 to 55 who have at least 12, but strictly less than 24 contribution months in the previous 5 years. In this group having at least 16 contribution months increases PBD from 6 to 8 months and having at least 20 contributions months increases PBD from 8 to 10 months. The long-eligibility group consists of workers between age 45 and 55 at the time of UI claim who had at least 30 months of UI contributions in the previous 5 years. Workers within this group who were younger than 50 at the time of UI claiming have 12 months of PBD while workers 50 or higher have 15 months of PBD.

The hazard rates for these groups (Figure 1a) display the familiar patterns with decreases in hazard from month 2 onward, and a spike near expiration. To show that these patterns are causal and not due to differences in sample composition, Figure 1b shows the regression discontinuity estimates of the hazard rate just before vs. just after the age cutoff that determines whether individuals have 12 or 15 months of PBD, displaying a sizable spike in the hazard rate near exhaustion. Regression discontinuity estimates comparing durations of 6 versus 8 month, and 8 versus 10 months display similar spikes (Online Appendix Figure A.3).

Recalls could explain the spike in the hazard at exhaustion if employers strategically choose recall dates to coincide with benefit expiration (Katz, 1986 and Katz and Meyer, 1990), and such recalls are important in settings such as the US (50% recall rate, Fujita and Moscarini, 2017) or Austria (35% recall rate, Nekoei and Weber, 2015). In contrast in our sample in Germany the share of UI recipients returning to their previous employer is only about 10-15% and the hazard rates excluding recalls are similar (Online Appendix Figure A.4).

In the survey, in addition to sampling by PBD strata, we also stratify the sample by elapsed nonemployment duration. For example, for the PBD=12 group, we contact some individuals at the end of the 2nd month after claiming UI, some at the end of the 5th months, and others at the end of the 8th, 11th and 13th month of unemployment duration. The weights are

[5] The technical aspect of sending SMS messages and processing responses was run by Guilherme Lichand at the University of Zurich and his company 'MGov' (now 'Movva').

chosen to oversample individuals close to the UI exhaustion point. Online Appendix Table A.2 shows the exact weights for the different cells. We call each of the Wave x PBD x D cells a "Panel". Figure 2b shows the 5 panels that start in November 2017 for the PBD=12 group, which each run for 4.5 months until March 2018.

In each of the following months until the start of the last wave in July 2019, we contacted new waves of workers following the same design. Thus, the same cohort of workers who had 2 months of unemployment duration in November of 2017 was contacted again in February 2018, now in the D=5 months panel. While we of course do not contact the same individual more than once, this **overlapping panel design** allows us to trace out search effort for a cohort of individuals for much longer than just the 18 survey weeks.

While the first 2 waves served as a pilot with only about 500 contacted individuals, we quickly increased this to first 3,000 and, starting in August 2018, to 5,000 contacted individuals per wave. Online Appendix Table A.3 provides more details for the contact dates and number of contacted individuals and participants for each of the 22 waves. With 5,000 individuals per wave we start to be constrained by the total number of individuals that are available in some of the strata. This is especially an issue in the PBD x D cells close to the exhaustion point, since those are larger and many people find jobs before exhausting UI benefits. This is a key reason for splitting the survey in so many waves, but a welcome side effect of this split is that it allows us to explore the role of calendar effects and time trends.[6]

Table 1 shows an overview of our sample. Column 1 shows average characteristics for all individuals who received UI benefits during our survey period. Workers without prior UI spells are eligible to exactly 6, 8, 10, 12, or 15 months of UI benefits (or even more if they are older than 55) at the beginning of their UI spell. Different PBD durations are possible for workers with prior UI spells and unused UI eligibility that they can carry over, or if workers participate in job training programs. Since we are interested in how search effort evolves around the UI exhaustion point, we restrict our sample to UI claimants who, at the time of sampling, have these exact levels as PBD. We also restrict to individuals with a cellphone number and a valid address, that are neither sanctioned nor in a training program at time of data retrieval. In addition, we restrict to age 28 to 55 at time of UI start, and in fact age 45 to 55 for the 12 and 15 PBD groups. Column 2 shows individuals that satisfy these sampling requirements and column 3 shows the characteristics of the 86,673 individuals contacted with a letter and then SMS messages. The differences between column 3 and 2 are due to the weights different PBD x D groups receive in our stratified sample.

[6]In the KM survey individuals were all contacted in a single wave, so that the UI entry date and the unemployment duration at survey start are essentially collinear.

Of the individuals contacted, Column 4 shows that about 9 percent agreed to participate. Given that individuals may not have read the letter/flyer, may not understand who is contacting them (and how we have obtained their cellphone number), and that we are asking them for permission to link their responses to sensitive personal information, this response rate strikes us as reasonable. It is comparable to the initial response rate in the KM survey (reported in the bottom row in Table 1). Comparing columns 3 and 4 it is clear that participation is not random. While the age composition is similar, participants are much less likely to be of foreign nationality (16 percent vs. 27 percent among the contacted), more highly educated and more likely to be women. The response rate across the different PBD groups is relatively similar.[7] Thus, below we provide robustness results re-weighting by these observables.

Due to the delay of 3-4 weeks between the most recent snapshot of the UI data to the contact date, 11.5 percent of participants have already found a job at the time of contact. We were concerned that participants might respond that they stopped looking for a job / found a job in order to cut the survey short. For that reason we make it clear that the survey continues whether or not the participants are employed and we keep everyone in the survey for the entire 18 weeks. Since we focus on the job search of the unemployed, column 5 shows the analysis sample of 6,877 participants who are unemployed at the beginning of the survey and respond to at least one question on job search. Conditional on participating in the first week, attrition is low: almost 70 percent (4,797) of the participants stay in the survey until week 18 and of those who stay about 61 percent are still unemployed (see column 5).[8] Furthermore the characteristics of individuals who participate initially are very similar to the participants who still participate at the end of the survey.

In addition to the biweekly questions on minutes spend on job search, we also ask one additional question each Tuesday, rotating between 4 questions:

1. **Target wage:** Please recall the last job you applied for. What do you think is the typical monthly wage for such a job in Euros?

2. **Life satisfaction:** Taken all together, how satisfied are you with your life? Please reply with a number between 1 (not satisfied at all) and 5 (very satisfied).

3. **Search intensity:** How hard did you search for a job over the last week? Please reply

[7] Online Appendix Table A.4 directly compares participants with non-participants and provides tests for equality. Due to sample sizes almost all differences are statistically significant.

[8] Online Appendix Figure A.5 shows that the attrition rate in our SMS based survey is substantially lower than in the KM study (about 50 percent by week 12). Furthermore, while KM report that respondents completed around 40 percent of the weekly interviews, in our data participants responded to around 78 percent of weekly job search questions, a likely benefit of using SMS messages as opposed to online questionnaires.

with a number from 1 (no search) to 10 (very hard search).

4. **Job Found:** We would like to know if your job search was successful. Please reply with 1 if you found a job and 2 if you are still searching for a job.

If a participant responds to the last question with “1”, we ask 3 follow up questions: a) what is the start date of the new job; b) what date was the offer received; and c) what date was the job accepted. Figure A.6 in the Online Appendix displays the sequence of the questions, while Table A.5 shows the complete text of all questions in German with English translation.

3 Validating the Survey Responses

3.1 Basic Patterns of Search Effort Responses

We now describe the basic pattern of responses to our main question on job search effort and provide suggestive evidence that the responses are meaningful and valid.

The question on job search effort, asked each Tuesday and Thursday for 18 weeks, is:

> How many hours did you spend searching for a job yesterday? For example, looking for job-postings, sending out applications or designing a cv. Please reply with the number of hours, e.g. “0.5”, or “2”. If, for whatever reason, you did not look for a job simply respond with “0”.

To deal with outliers (which may stem from mistyping a response), we drop all answers of job search above 15 hours (0.1 percent of observations) and winsorize the responses between 6 and 15 hours (2 percent of observations) to 6 hours. Figure 3a shows a histogram of all valid responses for unemployed job seekers transformed to minutes of job search. About 30 percent of the responses indicate no job search on the previous day. Given the phrasing of the question, almost all responses are at multiples of 30 minutes with bunching at full hours. Conditional on searching, the most common response is “1 hour”, but many people also report search effort between 30 minutes and 3 hours.

Figure 3b shows that the average search effort by day over the duration of our survey displays no obvious time trend and only limited seasonality.[9] Encouragingly, the mean time spent searching in our sample of 83 minutes is comparable to the average search intensity in the KM survey (70 minutes on weekdays), in the Survey of Consumer Expectations supplement

[9] If a person responds to a question the following day, we still code the response for the day that we originally asked about (for example Monday if the question was sent out on Tuesday but answered on Wednesday).

(77 minutes, Faberman et al., 2017) and is somewhat higher than in the American Time Use Survey (48 minutes, Krueger and Mueller, 2010).[10]

As a first validation check we investigate how search effort changes on public holidays, where we expect people to search less either because of holiday activities or since employers may not be reachable. While we paused the survey during the 2 weeks of Christmas / New Year in each year, we did ask questions on several days where the previous day was a national holiday, such as Easter Monday or Labor Day (May 1st). On these days, indicated in Figure 3b with dashed vertical lines, there is a clear dip in search effort. An event-study analysis (Figure 4a) shows a dip of around 30 minutes in search effort on a holiday.[11]

For a second validation check we use the fact that 1,858 respondents report finding a job during the survey period and provide job acceptance dates. Figure 4b shows that, while search effort is stable before job acceptance, it falls sharply to about 25 minutes after job acceptance. These 25 minutes are somewhat higher than the reported search intensity of employed workers in Faberman et al. (2017) of about 10 minutes, but this may be explained by the fact that accepted jobs in our sample could involve unattractive jobs, such as part-time jobs.

As a further check, Figure 4c shows how search effort evolves before and after the start of a job, splitting by the gap in days between the job offer and the job start. Workers who receive an offer and start a job shortly after (within less than 9 days) have the sharpest drop in search with search effort. If workers received an offer more than 26 days before the job start, search effort falls already around 2 months prior to the job start.[12]

Overall, search effort responds in sensible and intuitive ways to exogenous events like holidays and endogenous events like job acceptances and job offers.

3.2 Systematic Reporting Bias

A different challenge for a survey measure of search effort is that there could be systematic reporting bias over the course of the survey. For example, respondents might be embarrassed to admit not searching for a job but this 'social desirability bias' may decline over time as respondents get used to the survey. Respondents might also develop survey fatigue and default to answer '0' (or something else) as the survey goes on.

[10] Krueger and Mueller (2012) using time use data report much less time spent on job search in European countries (5-16 minutes). However these numbers do not condition on UI eligibility and likely include many long-term unemployed that make these less comparable to our sample.

[11] Online Appendix Table A.6 shows that search effort drops less for less important holidays, by around 17 minutes on regional holidays and by about 5 minutes during school vacations.

[12] Online Appendix Figure A.7 shows the distribution of the offer-start gap. It also shows that most of this gap comes from a gap between the job acceptance date and the job-start date and only to small degree from a gap between the job-offer date and the job-acceptance date.

We now consider this issue, with additional detail in Online Appendix D. Table 2 presents regressions of search effort (while unemployed) on the number of months of unemployment. The first columns ("between") use only the first response of each individual and the variation in unemployment duration is thus entirely cross-sectional, with controls added in Column 2. Column 3 ("within") uses all the responses but controls for individual fixed effects, thus presenting a within-person estimate. The point estimate for the between estimators is -0.44 minutes per month of job search , -0.51 with controls. The within estimate in column 3 is very similar, with a point estimate of -0.24, not statistically significantly different from the between estimate.

These findings are in sharp contrast to the corresponding specifications in KM which we replicated with the publicly available data in Columns 4-6.[13] While the between estimates in KM show a slight increase in column 4 (0.83 minutes per month), the within estimate in Column 6 implies a 10.78 minute decline per month. This discrepancy in within and between estimates shows up as a seesaw like pattern in KM Figure 3 (reproduced in Online Appendix Figure A.8), where each cohort starts with high search effort which subsequently declines until the start of the next cohort. This discrepancy makes it hard to draw clear conclusions whether search effort is in fact declining or flat throughout the unemployment spell. While within-person estimates have the advantage that the evolution of effort over time is not affected by changes in the sample, this advantage is negated in the presence of systematic reporting bias.

The corresponding figure in our data, Figure 5, shows that subsequent cohorts largely line up, i.e. the next cohort on average starts at a level of job search where the previous one ended. While there are some differences due to sampling error, they do not appear to be systematic.

We can also conduct a direct test of reporting bias based on the following intuition. Within a cohort of individuals who become unemployed at the same time and with the same PBD, it is random whether the person was sampled in an early or later strata of our survey. Suppose we observe two individuals with the same UI entry date T^{UI}, the same PBD P at a time t, but who were sampled at a different time (indicated by the survey contact date $T^{contact}$). In the absence of a survey reporting bias, how long an individual has been on the survey $t - T^{contact}$ should not be correlated with search effort s_t: $Cov(s_t, t - T^{contact} | t, T^{UI}, P) = 0$. We test this in Panel B of Table 2. We estimate a relatively small and statistically insignificant impact of the number of months in the survey on the reported search effort and the resulting point estimate is indeed very close to 0 and, despite small standard errors, statistically insignificant.[14]

[13] This corresponds to Table 2 in KM. In the paper the regressions add some controls from administrative data that are not publicly available which yields small differences to our results.

[14] Since KM had a single contact date, there is no variation in $t - T^{contact}$ conditional on t and T^{UI} and the test cannot be performed directly in their data.

We believe that the simplicity of the SMS method that was designed to make responding as easy and painless as possible and minimized the (true or perceived) incentives to simply respond with "0", largely avoids systematic reporting bias. While we cannot rule out that there is systematic bias in levels (e.g. search effort might always be overstated by 20 percent), any such bias does not appear to vary systematically over the course of the interview. Thus, in the next section we use the within-person response to search effort questions over time to examine how search effort varies throughout the unemployment spell and around UI exhaustion.

While the mean search effort is our key measure of search effort, we also present results on additional job search variables, namely different quantiles of the search effort measure, as well as the impact on three additional search variables which we ask once a month. Online Appendix Table A.7 presents the same test as in Table 2, Panel B for these additional variables. After replicating the test for our main variable in Panel A, in Panel B we present the result for a qualitative measure of job search, for the log monthly target wage, and for a life satisfaction measure. Unlike for our main measure, the qualitative search intensity measure displays a decrease over the survey, with some evidence of a decrease also for the life satisfaction variable. Panel C also shows that, while the average search effort displays no seesaw pattern, there is some pattern for some of the quantiles (such as whether the person searched at least 240 minutes). Thus, when we present these robustness results, we present also results adjusted, to a first approximation, for this survey trend.

4 Job Search over the Unemployment Spell

We now turn to three key pieces of evidence. First, we document the path of search effort in the initial months, far from exhaustion. The standard model predicts an increase, while other models predict a decrease, say due to discouragement or habituation. Second, we provide evidence on the path of search effort near exhaustion. The standard model predicts an increase up to exhaustion, with a constant effort thereafter. A reference-dependent model with a backward-looking reference point (DellaVigna et al., 2017) also suggests an increase up to exhaustion, but a decrease thereafter. For these analyses, we use the search effort responses, excluding individuals after the date at which they report having accepted a job offer.

Third, we focus on a test for the role of storable offers. Namely, we test whether individuals who report getting a job near benefit expiration are more likely to have lower search effort in the weeks beforehand. In the same spirit we test whether individual who receive job offers before UI exhaustion delay the job start date to the exhaustion point.

4.1 Job search at the beginning of the unemployment spell

For the first finding, we consider the intensity of search effort from month 2 (as early as we could survey unemployed respondents) to month 6, excluding the group with UI expiration at month 6. Figure 5 presents the disaggregated evidence separately for each of the five different PBD groups (6, 8, 10, 12, and 15 months), for each of the different sampling schemes. In all five PBD groups, the unemployment duration in the initial months is fairly flat, with a slight decrease for PBD of 8 and 15 months and a slight increase for PBD of 12 months.

In Table 3 we aggregate across all the PBD durations, except for PBD of 6 months, in which case it is difficult to separate the initial patterns in search effort versus the response to the upcoming expiration. We compare the search intensity in months 3, 4, 5, and 6, with search intensity in month 2 (the omitted category). Columns 1 and 2 display the estimates from a cross-sectional regression, combining within-person and between-person variation, with demographic controls added in Column 2. Both specifications indicate a flat profile of search effort. In Column 3 we add person fixed effects, thus focusing on within-person search effort. Finally, Column 4, our benchmark specification (reproduced in Figure 6a), also adds some basic time controls–fixed effects for question asked on Thursday versus Tuesday and calendar month fixed effects.[15] These specifications confirm the finding from the cross-sectional specification of a precisely-estimated flat search profile: we can reject a 5 percent (4.3 minutes) decrease in search intensity by month 6 relative to the search intensity in month 2.

How do these patterns compare with the patterns in the hazard from unemployment? Figure 6c displays a weighted hazard rate over PBD groups, matching the share of PBD groups in Figure 6a. Given the timing evidence in Figure 4b-c, we compare the patterns of job search to patterns in the hazard one month later. The flat path in search effort contrasts with a sharp decrease in the hazard rate from 12 to 7 percent over the same unemployment length. This suggests that the decline in hazard rates is unlikely to be due to a discouragement effect and may be due to unobserved heterogeneity.

4.2 Job search around UI exhaustion

For the second finding, we focus on search effort in the 4 months around the UI exhaustion. Most models, other than a pure storable-offer model, predict an increase in search effort up to expiration due to the (waning) option value of unemployment. Following expiration, the standard model predicts a flat profile of search intensity, or an increasing profile, to the

[15]Notice that we cannot add a full vector of date fixed effects, given the presence of individual fixed effects in the regression, for the usual inability to non-parametrically separate out cohort-time-age fixed effects.

extent that the workers are further depleting their assets. A model with reference dependence, instead, predicts a decrease in search intensity post expiration.

The disaggregated raw data on search intensity in Figure 5 shows evidence of an increase in search intensity up to expiration (captured as month T-1) for the PBD group 10, 12, and 15 months, with a flat pattern for 6 and 8 months. Following benefit expiration, search intensity declines for for PBD group 6, 10 and 12 months, and is flat for the other groups.

Table 4 presents the evidence for search intensity, compared to month T-1, the last month of receiving benefits, for cross-sectional specifications (Columns 1 and 2) and within-person specifications (Columns 3 and 4). These estimates yield similar results, provided we control at least for the basic demographic controls (Column 2). In the benchmark specification (Column 4), search effort increases by 7.3 minutes (s.e.=2.0 minutes) in the 3 months leading up to expiration, and then decreases by 5.8 minutes (s.e.=1.9 minutes) in the ensuing 3 months.

Figure 6b displays the point estimates from Column 4, comparing them to the parallel estimates on the time path of the hazard rate (Figure 6d). The "spike" in hazard is matched by a similar "spike" in search intensity, even if, in percent terms, the increase in minutes searched is clearly smaller. Unlike our conclusions in the previous section, this suggests that the hazard patterns at expiration *can* be accounted for by shifts in search effort, a point we return to in the section on estimates of job search models.

4.3 Robustness

We present a battery of robustness checks in Tables 5 and 6 for our two key results on search effort. All estimates include person fixed effect and time controls, as in our benchmark.

Sample Inclusion. The first two robustness checks address alternative ways to define who remains in the sample as the survey progresses. In Column 2 we restrict to "full participants" who respond (and stay unemployed) for the full 18 weeks. Next, we present a narrower definition of non-employment. It is important to exclude from the search measure individuals who found a job, and there may be some slippage in how we record this. In Column 3 we require that individuals actively report not having found a job. That is, while in our benchmark measure we presume that individuals are employed if they do not respond to the question on whether they are employed, in this sample we exclude those responses. The results from both samples (also in Online Appendix Figure A.9) are similar to the baseline ones.

Coding of Search Measure. In the benchmark, each observation is a survey response. In Column 4, we average all the responses of a respondent within a 2-week period and run the regressions at this bi-weekly level, effectively under-weighting responses by frequent responders. Next, in Column 5 we return to the response-level sampling, but aim to address the role of non-response, by coding as zero cases in which the individuals do not respond to a survey, provided that they give later responses, and that they confirm that they are still non-employed. In Columns 6 and 7 we vary the top-coding of the survey response to a lower threshold at 240 minutes (Column 6) or to a higher threshold (Column 7). In all four of these specifications, the results are similar to the baseline ones.

Extra Control. Another concern may be that since we cannot control for a full vector of time fixed effects (due to the inability of separately identifying a linear time and duration trend), the results may be partly driven by changes in labor market conditions over time. In Column 8, we thus estimate our baseline regressions also controlling for the county level monthly unemployment rate, yielding very similar results.

Representativeness of Sample. Table 1 showed that participants tend to have more education, are more likely to be German citizens and somewhat more likely to be female, compared to non-participants. Thus, we reproduce our results reweighting our sample to match the composition of the sample frame (Column 9) and of the overall pool of unemployed (Column 10). We find similar results, with a stronger increase in search effort up to expiration and a smaller (though still clear) decline in search effort after expiration. In Online Appendix Tables A.8 and A.9 (with results reproduced in Online Appendix Figures A.10 and A.11) we present the results split by different demographics. We find the same qualitative patterns across the groups, though some groups display more evidence of an increase up to exhaustion, while other more evidence of a decrease ex post.

Different PBD Groups. A legitimate question is whether a single PBD group is responsible for the estimated search effort patterns. In Online Appendix Table A.10, we estimate the patterns for search intensity around expiration for the 5 groups. We detect a clear increase in search effort leading up to the expiration for 3 out of the 5 groups (and a flat pattern for the other 2). Similarly, we observe a decrease in search effort post expiration for 4 out of the 5 groups, with an increase just for the 15-month PBD group. As Figure 5 shows, the pattern of flat search effort over the initial month holds for 4 out of the 5 groups. Thus, while we pool the PBDs for statistical power, the results are not reliant on any one group.

Distribution of Search Effort. So far we have considered our main envisioned measure, the average reported search effort in minutes. It is valuable, though, to also consider shifts at different quantiles of the distribution, such as the share of workers reporting positive search, the share reporting search for at least 240 minutes, and so on. Online Appendix Figure A.12 and A.13 display the disaggregate plot of the share of such searches. Unlike for our main measure, these figures provide evidence of apparent survey bias, in that the share reporting positive search declines within a cohort more than it does between cohorts, with the opposite for the share reporting search above 240 minutes.[16] Panel B in Online Appendix Table A.7 indeed estimates a significant within-person impact of survey duration, negative for any search and positive for search above 120 minutes. Thus, in Online Appendix Tables A.11 and A.12 which replicate the key tables on initial search effort and effort around expiration for these quantile variables, we display in Panel B the estimates with a linear correction for the survey bias. While the unadjusted estimates display quite different patterns across the different quantiles, after adjustment for the survey bias in Panel B, the results are consistent with the main ones: in the initial months of unemployment the search intensity is flat, or slightly decreasing (Table A.11). Around expiration, search intensity increases up to expiration (weakly for the any-search measure) and decreases following expiration (Table A.12).

Additional Search Measures. While the focus of the survey is on the measure of minutes of job search, the question we ask twice a week, we also rotate 3 additional questions related to job search, each of which is asked every 4 weeks: a qualitative 1-10 measure of search intensity, a measure of target wage (which we transform in logs), and a measure of life satisfaction. Online Appendix Figures A.15, A.16 and A.17 display the raw patterns for these three variables, showing for the qualitative search intensity variable a clear within-survey downward trend. Indeed, Panel C of Online Appendix Table A.7 confirms that this is the case for two of the three measures, including the qualitative search measure.[17] In Online Appendix Table A.13 and A.14 we provide the within-person results for these measures in the initial months and near expiration. An important caveat is that these measures are significantly more noisy, given that each individual gives at most 4 responses in the sample. After controlling for the survey response bias (Panel B), the results for the qualitative search effort measure are consistent with the main ones: the search effort is quite flat in the initial months, and it is increasing up to expiration and (weakly) decreasing thereafter. The log target wage is fairly flat in the initial month, consistent with the findings in Krueger and Mueller (2016), it decreases slightly up to expiration, as predicted, and then it slightly decreases further. Life satisfaction appears to decrease in the initial months, though the pattern is not obvious with the survey correction (Panel B). Overall, these results are less clear than the benchmark ones, but this is to be expected given the infrequency of these questions in our sampling, as well as the evidence of some survey response bias (unlike for our main measure).

[16] Online Appendix Figure A.14 validates these measures, showing that they respond to job acceptance.

[17] Online Appendix Figure A.18 shows that the qualitative search measure and the life satisfaction measure respond as expected to job acceptance, while, surprisingly, we detect no response for the log target wage.

4.4 Do job seekers time the start date of a job with the exhaustion of benefits?

We then turn to our third key finding on storable offers: the spike in the hazard at expiration may be mostly due to unemployed workers who received an offer earlier on in the spell, but opted to delay the start of work until the end of the UI benefit period. As far as we know, while this explanation has been put forward often, there is little direct evidence to it.

As a first piece of evidence on this explanation, we use as measure of storable offers the distance in days between the date a job offer was received and when the job started, as reported to us by the workers, censoring this measure at 180 days. To the extent that storable offers explain the spike, this delay in starting a job should be larger for individuals who start a job at UI exhaustion, versus individuals who start a job before exhaustion, or after exhaustion. Figure 7 and Online Appendix Table A.15 show the evidence in this regard. The average delay between job offer and job start varies mostly between 25 and 30 days for individuals taking jobs in month -4 to -1 before expiration, and 1 to 2 months after expiration. For the 251 individuals who start a job in the month of UI expiration, this delay is in this range, at 28.4 days. This evidence suggests that delay of job start due to storable offers, if any, is limited to a small share of workers, or would have to be very limited temporally.

As a complementary piece of evidence, in Figure 7b we examine the timing of the search effort intensity in the months leading up to the job start for individuals who start a job at expiration, versus individuals who start a job before, or after, UI expiration. To the extent that storable offers are common for the group starting a job at UI expiration, we should see their search effort taper off sooner. Instead, Figure 7b shows that the patterns of decrease of search effort leading up to job start are very similar, independent of when the job start falls. Thus, under either measure we do not find evidence supporting a quantitatively important role for storable offer models in explaining the spike at expiration.

4.5 Contrasting the results with expert forecasts

How do these results line up with the expectations of job search experts? What role did experts anticipate for storable offers, discouragement, and other models in search effort? Along the lines proposed by DellaVigna and Pope (2018) and DellaVigna et al. (2019), we elicit expectations for the three key findings above. We identified 48 job search experts from papers in the area in high-impact journals in the last few years, or more junior researchers working in the area. We then contacted these researchers asking whether they would be willing to answer a prediction survey taking 10-15 minutes on our job search findings. We are grateful to the 35 experts who completed the survey, for a 74 percent participation rate.

The survey presented the set up with some key summary statistics, and then asked for prediction for 4 key numbers, corresponding to the 3 key findings. First, we provided the average search effort in month 2 of unemployment, and asked for a prediction for month 6 (our first finding). Second, we provided the search effort for the month before expiration and we asked for the search effort in month -4 (to measure the expected increase in search effort up to expiration, if any), and in month +2 (to capture an possible decrease of search effort post expiration). Finally, for the storable offer finding, we presented Figure 7a without showing the observation for individuals who find a job in month 0, and asked for a prediction for that.[18]

Figures 8a-c present the average forecast, compared to the findings, with additional information in Appendix Table A.16 and the full distribution of forecasts in Online Appendix Figure A.19. The experts on average expect a 20 percent decrease in search effort from month 2 to 6, well outside the confidence interval of the actual findings (Figure 8a). Thus, they expected either a larger role for discouragement or for reference dependence, than we observe.

The experts also expect a sizable increase in search effort leading up to expiration, as predicted by most models except for a pure storable-offer model (Figure 8b). Thus, the experts do not believe that the "spike" is purely due to storable offers. The expert also expect a similar-sized decrease in search effort post expiration, as predicted under reference dependence, but not under the standard model. These predictions are directionally in line with the data, even though the experts overestimate the extent of the spike in search effort.

Finally, the experts on average expect an offer-start gap over 50% larger for individuals who start a job at UI expiration, compared to in other periods (Figure 8c). Thus, the experts expect a larger incidence of storable offers than we observe in the data.

5 Reconciling the Survey Results with Job Search Models

To interpret the findings, we estimate a non-stationary job search model (van den Berg, 1990) using as moments both the search effort and the hazard patterns. The model builds on DellaVigna et al. (2017) allowing for reference dependence and present bias, but spells out separately the cost of effort and the productivity of effort. The model has a search effort margin and an optimal consumption choice, but no reservation wage choice. It allows for unobserved heterogeneity in the effort cost and in the search productivity functions.

[18] The figures and numbers presented to the experts were not exactly identical to the ones in the paper due to some further data cleaning that occurred after the survey. However, the differences are minor.

5.1 The job search model

Model Setup. We make several simplifying assumptions. First, jobs last indefinitely once found. Second, wages are fixed, eliminating reservation-wage choices. In each period t an unemployed worker sets the optimal effort e_t (e.g. minutes of job search per day). The effort is linked to a probability of obtaining a job offer in period t by the function $f(e_t)$. That is, with probability $f(e_t)$ the individual obtains a job paying a re-employment wage w. If the individual accepts the job offer, the job starts in period $t+1$. Search effort is costly, with a cost of effort $c(e_t)$. We assume $c(0) = f(0) = 0, c'(e) > 0, f'(e) > 0, c''(e) > 0$.

In each period, individuals receive income y_t, either UI benefits b_t or wage w_t, and consume c_t. Consumers can accumulate (or run down) assets A_t with a borrowing constraint $A_t \geq -L$. Assets earn a return R so consumers face a budget constraint $\frac{A_{t+1}}{1+R} = A_t + y_t - c_t$. The UI benefits b_t equal $b_t = b$ for $t \leq P$ and $b_t = \underline{b}$ for $t > P$. In each period t individuals choose not only the search effort but also the optimal consumption c_t, yielding utility $u(c_t)$.

The utility from consumption is potentially reference-dependent:

$$u\left(c_t|r_t\right) = \begin{array}{ll} v\left(c_t\right) + \eta\left[v\left(c_t\right) - v\left(r_t\right)\right] & \text{if} \quad c_t \geq r_t \\ v\left(c_t\right) + \eta\lambda\left[v\left(c_t\right) - v\left(r_t\right)\right] & \text{if} \quad c_t < r_t \end{array} \tag{1}$$

where r_t is the reference point. The utility consists of consumption utility $v\left(c_t\right)$ and gain-loss utility $v\left(c_t\right) - v\left(r_t\right)$. When consumption is above the reference point ($c_t \geq r_t$), the individual derives gain utility $v\left(c_t\right) - v\left(r_t\right) > 0$, which receives weight η, set to 1. When consumption is below the reference point ($c_t < r_t$), the individual derives loss utility $v\left(c_t\right) - v\left(r_t\right) < 0$, with weight $\lambda\eta$. The parameter $\lambda \geq 1$ captures loss aversion: the marginal utility is higher for losses than for gains. The standard search model is nested in this model for $\eta = 0$.

As in DellaVigna et al. (2017), the reference point is the average income over the $N \geq 1$ previous periods:

$$r_t = \frac{1}{N} \sum_{k=t-N}^{t-1} y_k.$$

The parameter N captures the length of adaption: the longer the N, the more an unemployed worker feels the loss utility from being unemployed relative to the earlier paychecks (with $w > b$) or, after the end of the UI benefit period, relative to the UI benefit checks.[19]

Value Functions. The unemployed choose search effort e_t and consumption c_t in each

[19] There are alternative assumptions for the reference point, in terms of past consumption or forward looking as in Kőszegi and Rabin (2006). DellaVigna et al. (2017) discuss these alternatives. A key advantage of our assumption of an income-based reference point is that it is computationally simpler, given that its path is exogenous, while capturing the key memory-salience motivation for backward looking reference points.

period and (assuming for now an exponential discount factor δ) face the value function:

$$\begin{aligned} V_t^U(A_t) &= \max_{e_t;A_{t+1}} u\left(c_t|r_t\right) - c\left(e_t\right) + \delta\left[f(e_t)V^E_{t+1|t+1}\left(A_{t+1}\right) + (1-f(e_t))V^U_{t+1}\left(A_{t+1}\right)\right] \quad (2) \\ & \text{subject to: } c_t = A_t + y_t - \frac{A_{t+1}}{1+R}. \end{aligned}$$

For the unemployed, the value function depends only on assets A_t, since the reference point is fully determined by t and thus is not an explicit state variable: $V_t^U(A_t)$.

For the employed, the value function is $V^E_{t|j}(A_t)$ for an individual employed in period t and who found a job in period j, where the combination of t and j determines the reference point:

$$V^E_{t|j}\left(A_t\right) = \max_{c_t>0} u\left(c_t|r_t\right) + \delta V^E_{t+1|j}\left(A_{t+1}\right). \quad (3)$$

Given Equation (2) the first order condition for the optimal level of search effort e_t^* in the case of an interior solution can be written as:

$$c'\left(e_t^*\left(A_{t+1}\right)\right) = \delta f'(e_t)\left[V^E_{t+1|t+1}\left(A_{t+1}\right) - V^U_{t+1}\left(A_{t+1}\right)\right]. \quad (4)$$

The optimal level equates the marginal cost of effort with the marginal value of effort, which in turn is equal to the marginal productivity of effort, times the difference between the value function of being employed, versus unemployed. Notice that the reference dependence affects the optimal effort though its impact on $V^E_{t+1|t+1}$ and V^U_{t+1}.

Given that the function $f(e)$ is monotonic, we can rewrite problem (2) as

$$\max_{s_t;A_{t+1}} u\left(c_t|r_t\right) - \widetilde{c}\left(s_t\right) + \delta\left[s_t V^E_{t+1|t+1}\left(A_{t+1}\right) + (1-s_t)V^U_{t+1}\left(A_{t+1}\right)\right] \quad (5)$$

where $\tilde{c}(s_t)$ is the composite of the actual cost of effort and the inverse of the production function: $\tilde{c}(s_t) = c(f^{-1}(s_t))$. This reformulation implies that the problem can be solved as if the optimization is with respect to the probability of exiting unemployment, s_t, as in DellaVigna et al. (2017). This also makes it clear that with just data on the hazard rate from unemployment s_t, one could not possibly separate out the function $c(e)$ and $f(e)$, as one instead estimates a composite function $c(f^{-1}(s_t))$. Finally, this clarifies that, in order to find an interior solution to (5), we need to assume $\tilde{c}''(s_t) > 0$, in addition to the previous assumptions (which guarantee $\tilde{c}'(s_t) > 0$).

We extend the model to allow for present-bias, with an additional discount factor $\beta \leq 1$ between the current period and the future. Following DellaVigna et al. (2017) and Ganong and Noel (2019), we assume naiveté: the workers (wrongly) assume that in the future they will make decisions based on regular discounting δ. This assumption simplifies the problem, since we can use the value functions of the exponential agent (given that the naive worker believes she will be exponential from next period). In addition, the evidence on present bias is largely consistent with naivete' (DellaVigna, 2009; Augenblick and Rabin, 2019). The naive present-biased individual solves the following value functions:

$$\begin{aligned} V_t^{U,n}(A_t) &= \max_{s_t\in[0,1];A_{t+1}} u\left(c_t|r_t\right) - \widetilde{c}\left(s_t\right) + \beta\delta\left[s_t V^E_{t+1|t+1}\left(A_{t+1}\right) + \left(1-s_t\right)V^U_{t+1}\left(A_{t+1}\right)\right] \quad (6)\\ & \text{subject to: } c_t = A_t + y_t - \frac{A_{t+1}}{1+R}, \end{aligned}$$

where the functions V^U_{t+1} and $V^E_{t+1|t+1}$ are given by equations (2) and (3) above for the exponential discounters. We thus first solve for all possible values of V^U_{t+1} and $V^E_{t+1|t+1}$ and then we solve for consumption and search paths given $V^{U,n}_{t+1}$.

5.2 Estimation

Parametric Assumptions. To bring the model to the data, we introduce a set of additional assumptions. First, we assume log utility, $v\left(c\right) = \ln\left(c\right)$. Second, we assume a search cost function of power form: $c\left(e\right) = ke^{1+\gamma}/\left(1+\gamma\right)$, with $\gamma > 0$ so the function is increasing and convex. Third, similarly we assume that the productivity of effort takes a power form $f(e_t) = min\left[1, Ee^{1+\zeta}/(1+\zeta)\right]$, with $\zeta > -1$ so that the function is increasing. This implies that the composite cost function $\widetilde{c}\left(s_t\right)$ equals $\widetilde{c}(s_t) = \frac{\widetilde{k}}{1+\widetilde{\gamma}}\left(s\right)^{(1+\widetilde{\gamma})}$ with $\widetilde{\gamma} = \frac{\gamma-\zeta}{1+\zeta}$ and $\widetilde{k} = \frac{k}{E}(\frac{1+\zeta}{E})^{\frac{\gamma-\zeta}{1+\zeta}}$. To guarantee an interior solution, we need $\widetilde{c}''(s_t) > 0$ and thus $\gamma > \zeta$, that is, the search cost function is more concave than the productivity of effort function.

Fourth, we model heterogeneity across workers as heterogeneity in both the cost of search k and the productivity parameter E. For example, when allowing for two types, we assume type 1 has parameters (k_1, E_1) while type 2 has parameters (k_2, E_2).

Fifth, we make the following assumption about the wages and unemployment benefits. We take the pre-unemployment wage w to equal the average wage for each of the different PBD groups.[20] We assume that the re-employment wage equals $0.9w$, building on evidence in Schmieder et al. (2016). We assume that UI benefits equal $0.635w$, and that following expiration of the UI system, workers receive welfare benefits equal to 400 euros. Sixth, we assume that individuals start with zero assets, that they cannot borrow against their future income, and that they earn no interest on savings (given the low-interest rate environment).

[20]For our baseline estimates with PBD=12 and 15 we assume a pre-unemployment wage of 1610 Euro per month. For the PBD=8 and 10 robustness check we assume a wage of 1265 Euro.

The vector of parameters ξ for the standard model are: (i) the three levels of search cost k_{high}, k_{med}, and k_{low}, with $k_{high} \geq k_{med} \geq k_{low}$, three levels of productivity of effort E_{high}, E_{med}, and E_{low}, and two probability weights p_{low} and $p_{med;}$ (ii) the search cost curvature γ; (iii) the productivity curvature ζ; (iv) the time preference parameters δ and β. For the reference-dependent model, we estimate in addition: (v) the loss aversion parameter λ; and (vi) the number of (1-month) periods N over which the backward-looking reference point is formed.[21] For the reference-dependent model we estimate a model with 3 types of heterogeneity, and a model with only 2 types of heterogeneity, in which case we remove parameters k_{high}, E_{high}, and p_{med}. The weight η on gain-loss utility is set to 1 rather than being estimated; thus, the loss-aversion parameter λ can be interpreted also as the overall weight on loss utility.

Estimation. Denote by $m(\xi)$ the vector of moments predicted by the theory as a function of the parameters ξ, and by $\hat{m}$ the vector of observed moments. The moments $m(\xi)$ combine the information on average search intensity in minutes from our survey, as well as the administrative information on the hazard rates. For the search intensity, we use the key findings on the within-person search effort path in months 2-6 (Figure 6a) as well as the within-person path around UI expiration (Figure 6b). In addition, in order to pin down the level of the productivity of effort across groups (E_j), we also add the average cross-sectional search effort in month 2 and at expiration (T).[22] For the hazards, we use the monthly hazard rates from month 2 to month 19 for the PBD group 12 and 15, computed using a standard regression discontinuity design exploiting the age discontinuity in PBD around age 50 (Figure 1b).

The estimator chooses the $\hat{\xi}$ to minimize the distance $(m(\xi) - \hat{m})' W (m(\xi) - \hat{m})$. As weighting matrix W, we weight the hazard moments with the diagonal of the estimated variance of the hazard moments; we weight the search effort moments with inverse of the variance-covariance matrix. We upweight the weight of the search effort minutes by a factor of 10, to recognize the focus of the estimation on the novel evidence on minutes, as well as the potential mis-specification of the hazard model with respect to the forms of heterogeneity.[23]

To calculate the theoretical moments, we use backward induction. First we numerically compute the steady-state search and value of unemployment. Then we solve for the optimal search and consumption path in each period as a function of the asset level. Finally, we use the initial asset level as a starting value to determine the actual consumption path and search intensity in each period.

[21] In the tables we report the speed of adjustment in days, that is, N*30.

[22] These moments do not affect the fit of the different models, as both standard and referent-dependent models fit them perfectly. They are, however, important to pin down the parameters for the different types, as they document the extent of unobserved heterogeneity in search effort over time.

[23] This is similar in spirit to Armstrong and Kolesár (2019).

Under standard conditions, the minimum-distance estimator using weighting matrix W achieves asymptotic normality, with estimated variance $(\hat{G}'W\hat{G})^{-1}(\hat{G}'W\hat{\Lambda}W\hat{G})(\hat{G}'W\hat{G})^{-1}/N$, where $\hat{G} \equiv N^{-1}\sum_{i=1}^{N}\nabla_{\xi}m_i(\hat{\xi})$ and $\hat{\Lambda} \equiv Var[m(\hat{\xi})]$.

5.3 Estimates

Benchmark Estimates. In Table 7, we present estimates for a 3-type standard model with no reference dependence ($\eta = 0$) in Columns 1 and 4, for a 2-type reference-dependent model in Columns 2 and 5, and for a 3-type reference-dependent model in Columns 3 and 6. For each of these models, we assume exponential discounting ($\beta = 1$) in Columns 1-3 and allow for present bias, fixing the long-term monthly discount factor to $\delta = 0.995$ (equivalent to an annual 6% discount rate), in Columns 4-6.

The estimates for the standard model present similar patterns. We estimate a high degree of impatience, especially for the exponential discounting case, with a monthly discount factor $\hat{\delta} = 0.639$, a fairly convex effort productivity function and an even more convex cost of effort function; the three types differ substantially in the cost of effort and productivity levels.

The estimates for the reference-dependent models similarly point to a convex effort productivity function and an even more convex cost of effort function, and also high impatience, with a monthly discount factor $\hat{\delta} = 0.897$ in Column 3 and a present-bias parameter $\hat{\beta} = 0.473$ in Column 6 (similar to the estimates in Paserman, 2008 and one of the types in Ganong and Noel, 2019). For both the 2-type and the 3-type reference dependent model, the estimates allowing for present-bias have a significantly better fit, in addition to more reasonable estimates for the discount parameters. Thus, we take the estimates in columns 5 and 6 to be our benchmarks. We estimate loss-aversion parameters $\widehat{\lambda} = 3.18$ and $\widehat{\lambda} = 2.66$, in the range of estimates in the literature.[24] The estimated parameters $\widehat{N} = 298$ and $\widehat{N} = 338$ (in days) indicate slow adaptation; this parameter is estimated to be about twice as long as in the Hungarian context (DellaVigna et al., 2017).

Figure 9 compares the fit of the 3-type standard model and the 3-type reference-dependent model, for the present-bias case (Columns 4 and 6). Interestingly, both models fit the path of the hazard very well, in particular capturing all the spike in hazard at UI expiration (Figures 9c-d). Thus, the two models would be hardly distinguishable based on the hazard alone. Turning to the search effort moments, both models fit quite well the path of the search effort

[24] Online Appendix Figure A.20 shows a clear improvement in fit as measured by SSE for the specification in Column 6 as λ increases from 1.5 to 2, and a flatter slope for higher λ. The figure also shows the SSE for the specification with exponential discounting in Column 3, which estimates a large $\hat{\lambda} = 12.6$. The figure shows that the fit is fairly comparable for $\lambda = 4$.

in the initial months of unemployment (Figure 9a). This may be surprising, since one may have expected the within-person search intensity to increase significantly in the standard model, and conversely to decrease in the reference-dependent model, reflecting the adaptation to the losses. In the standard model, though, the increase of search effort is convex and slow initially, especially given the high discounting. For the reference-dependent model, the flat initial path reflects the countervailing forces of a decrease in effort due to the initial (slow) adaptation, but also an increase due to the envisioned upcoming loss at UI expiration.

The key difference between the two models is in with regards to the search effort at expiration (Figure 9b). The standard model fits well the increase in search effort up to expiration, but cannot capture the decrease post-expiration. In fact, notice that to the extent that the agents smooth consumption and thus still have some assets at expiration, the within-person search effort would keep *increasing* post expiration, as the individuals deplete the remaining assets. This contributes to the estimated high impatience in the standard model.

In contrast, the reference-dependent model fits well not just the increase in search up to expiration—due not just to the usual option value but also to the anticipated loss utility due to loss in benefits—, but also the observed decrease in effort part expiration. In the months following the UI exhaustion, the habituation moderates the loss utility due to the cut in benefits, accounting thus for the lower search intensity. Importantly, the model fits the observed decrease in search effort for a reasonable (if sizable) degree of loss aversion.

Online Appendix Figures A.21 and A.22 display the fit for some of the other models in Table 7. The 3-type models assuming exponential discounting (Figure A.21) display similar qualitative features, though the fit of the hazard moment is not quite as good as under the present-bias assumption. The estimates with present-bias but assuming just 2 types for the reference-dependent model (Figure A.22) do not fit the hazard spike or the decline in search effort post UI expiration quite as well as in the benchmark, but overall already provide a better qualitative fit than the 3-type standard model, despite having fewer parameters.

Robustness. In Table 8 we present a number of alternative specifications, taking as benchmarks the 3-type standard model with present bias (Column 4 of Table 7) and the 3-type reference-dependent model with present bias (Column 6 of Table 7). We first vary key model assumptions. In Column 1, we estimate both β and δ: we cannot reject a $\delta = 0.995$ (as assumed earlier) and do not obtain a better fit of the data compared to the benchmarks. In Column 2, we estimate the gain utility parameter η instead of fixing it to 1, as typical in the literature. We estimate a larger $\hat{\eta} = 4.24$, with a correspondingly smaller λ, not surprisingly since the extent of loss aversion is essentially $\eta * (\lambda - 1)$. Since the fit for this model is only slightly better than for our benchmark, we maintain the assumption $\eta = 1$.

In Column 3, conversely we present estimates from a linear reference-dependent model, with $\eta > 0$ but no loss aversion ($\lambda = 1$). Even without loss aversion, reference dependence still has an impact on job search because a high reference point increases differentially the value of employment relative to the value of unemployment. The fit of this model, while clearly superior to the standard model, is not as good as with loss aversion (SSE=140.7 versus 129.2), and in particular it does not fit the decline in search effort after UI expiration very well (Online Appendix Figure A.23). In Column 4, we remove the assumption of 0 initial wealth (consistently with the high estimated impatience) and assume assets equal to one month of pre-unemployment income. The qualitative features of the estimates are unchanged, with a slightly worse fit for both the standard model and the reference-dependent model.

In the next three specifications, we vary the moments used. In Column 5, we use the same moments, but we do not upweight the search effort moments, using instead (the diagonal of) the optimal weighting matrix, thus giving much more weight to the hazard moments (estimated on much larger administrative data). The qualitative patterns are similar, with a better fit for the reference-dependent model (SSE=69.7 versus 106.8), which however now fits only partially the decline in search effort post expiration. In Column 6, we revert to the benchmark weighting, but we exclude from the estimation the search effort moments for the months past UI expiration. Without these moments, we cannot reject the null of no loss aversion ($\lambda = 1$), indicating the importance of the expiration moments for the identification of reference dependence. Finally, in Column 7 we use the benchmark search effort moments but instead of using the hazard moments for the 12 vs. 15 month PBD, we use the hazards for the 8 versus 10 month PBD. As Online Appendix Figure A.24 also shows, the reference-dependent model has a clearly better fit than the standard model (SSE=197.0 vs. 340.6).

6 Discussion and Conclusion

In this paper, we present novel evidence on the search effort of unemployed workers from an SMS-based survey of unemployed workers in Germany. We present three key findings on within-person search effort over the spell. First, the intensity of job search is flat in the initial months of unemployment, from month 2 to month 6. Second, in the months surrounding UI expiration search effort first increases up to expiration and then decreases thereafter. Third, we do not find evidence that workers starting a new job at UI expiration had an offer earlier, or stopped searching earlier, as hypothesized under a storable-offer model.

We estimate a model that allows for unobserved heterogeneity in both the cost of search and in the productivity of search effort, using as moments evidence from the survey and on the hazard into employment from matched administrative data. We allow for reference dependence with respect to recent income, to capture a form of backward-looking reference dependence. While both a standard model and a reference-dependent model fit well the path of the hazard and the flat pattern of search effort in the initial months, only the reference-dependent model can explain the increasing and then decreasing pattern of search effort around UI expiration.

The model that we estimate focuses on a comparison of a standard model with unobserved heterogeneity with a reference-dependent model. Yet, a variety of other models have been proposed in the literature to understand observed patterns in job search. A first set of models aims to explain the spike at expiration with storable offers; as we discussed above, we do not find evidence supporting this model in the German context, and our structural estimates can explain the full extent of the spike, without resorting to storable offers. We should notice that this may differ in other contexts. In the Hungary context (DellaVigna et al., 2017), for example, neither the standard model nor the reference-dependent model fit well the spike in hazard at UI expiration. It remains an open question whether storable offers may be more common in a different institutional context such as in Hungary.

A second explanation for the spike at expiration involves recalled workers going back to their jobs. In our context, though, recalls are not common, and we show that the hazard patterns are similar if we exclude recalls.

A third explanation for the search effort patterns is that there may be only a fixed set of jobs to search for and that, after an unemployed worker has gone through them, the worker does not have much scope for additional job search. This could in principle explain why after UI expiration, when presumably workers are search especially intensely, search intensity may decline. Yet, this explanation would predict a temporary decrease in search effort right after UI expiration, not a continuous decrease. Furthermore, if such lumpy nature of search effort were of first-order importance, it likely would manifest itself also in a decrease in search effort over the initial months. We stress that such lumpy search effort patterns may be more of a first-order issue for methods that measure only one type of search effort, such as possibly online postings, than for a measure that aims to capture all margins of search effort, like ours.

A fourth explanation is worker discouragement, perhaps because of a decline in the call back rate over the spell. This could explain the decrease in search effort after expiration. However, to the extent that there is a discouragement effect, one would expect it to be stronger in the initial months (as in Kroft et al., 2013), when instead search intensity is flat.

Of course, it is possible that a combination of such explanations is at play, in a way that would explain the overall findings. In any case, we hope that the additional evidence on within-person search intensity will prove useful in providing additional facts to tease alternative models apart. As we stressed in the paper, the fact that we can consider within-person patterns enables us to largely side-steps concerns about unobserved heterogeneity that plays a key role in understanding the patterns in hazard rates from unemployment.

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Table 1: Summary Table

	(1) All UI Recipients	(2) Sample Frame	(3) Contacted	(4) Participants Month 1	(5) Participants Month 1 Unemployed	(6) Participants Month 4 Unempl. Month 1
Demographics						
Female = 1	0.45	0.46	0.45	0.50	0.50	0.50
Age	42.03	44.42	43.28	43.06	43.22	43.44
Non-German Nat.= 1	0.18	0.22	0.27	0.16	0.17	0.13
Education Missing	0.30	0.31	0.36	0.23	0.24	0.21
Low Education	0.56	0.54	0.49	0.50	0.50	0.51
High Education	0.13	0.15	0.15	0.26	0.25	0.27
cellphone == 1	0.79	0.99	1.00	1.00	1.00	1.00
UI Characteristics						
P at UI start = 6 months	0.04	0.16	0.24	0.23	0.22	0.22
P at UI start = 8 months	0.03	0.13	0.21	0.20	0.19	0.19
P at UI start = 10 months	0.03	0.11	0.17	0.18	0.18	0.17
P at UI start = 12 months	0.24	0.36	0.21	0.22	0.22	0.23
P at UI start = 15 months	0.05	0.24	0.17	0.17	0.18	0.19
P at UI start = 18 months	0.03	0.00	0.00	0.00	0.00	0.00
P at UI start = 24 months	0.07	0.00	0.00	0.00	0.00	0.00
P at UI start = other	0.52	0.00	0.00	0.00	0.00	0.00
Nonemp. Duration in months (at last contact)	6.23	5.91	6.62	6.41	6.49	6.56
Survey Outcomes						
Min. Searched Yesterday				76.00	81.43	65.09
Reported Life Satisfaction (Scale 1 to 5)				3.22	3.15	3.21
Censored Reservation Wage				2758.84	2727.92	2747.34
Search Intensity (Scale 1 to 10)				4.88	5.25	4.14
Unemployed = 1				0.88	1.00	0.61
N	2982951	377015	86673	7797	6877	4780
Krueger-Mueller Data*	362292	63813	63813	6025		

Notes: This table summarizes characteristics of the stock of UI recipients at different stages of the sampling process. Column (1) shows all UI recipients for all waves the survey was running. Column (2) shows all individuals that fulfill the basic sampling requirements. Column (3) represent the actually contacted individuals, which are a stratified random sample based on PxD cells. Column (4) contains all individuals that participated initially in the survey, column (5) shows participants that were also unemployed and column (6) shows individuals that were initially unemployed and still participated in the last month of the survey. Survey outcomes (except job search) contain first (columns 4 and 5) and last (column 6) observation of each participant.
*Numbers retrieved from tables and text in Krueger and Mueller (2011).

Table 2: Tests for Survey Response Bias

	(1)	(2)	(3)	(4)	(5)	(6)
	German SMS Data			Krueger-Mueller Diary Data		
Panel A: Test for Survey Response Bias in SMS and KM-Data						
	First Survey Response		All Responses	First Survey Response		All Responses
	Between	Between w/ controls	Within	Between	Between w/ controls	Within
Months Unemployed	-0.440	-0.515*	-0.239	0.826*	0.502	-10.778***
	[0.296]	[0.311]	[0.297]	[0.458]	[0.429]	[0.960]
Adj.R^2	0.00	0.03	0.49	0.07	0.11	0.67
Mean Job Search	79.11	79.11	84.74	102.11	101.74	64.71
N Individuals	6733	6733	6733	4202	4124	4813
N	6733	6733	119409	4202	4124	25658
p-Val. Col. (2) vs. (3) /(5) vs. (6)			0.471			0.000
Individual Controls		X			X	
Individual FE			X			X
Panel B: Direct Estimate for Survey Response Bias						
Survey Duration in Months	0.814	1.053	0.943			
	[0.661]	[0.712]	[0.688]			
Adj. R^2	0.002	0.007	0.040			
Mean Dep. Var	84.896	84.896	84.896			
N Individuals	6877	6877	6877			
N	121405	121405	121405			
P-Group x Unemp. Dur. FE	X	X	X			
Time (running week) FE		X	X			
Individual Controls			X			

Panel A performs the test for survey response bias as outlined in Krueger-Mueller (2011), applied to the German SMS-data (columns (1) to (3)) as well as to the original K&M data (columns (4)-(6)). In column (1)-(2) and (4)-(5) of Panel A, we only use the first response to the job-search question, conditional on that this response happens within the first week after survey start. Unemployment duration is the difference between UI-entry and the day of the interview (scaled to months). Standard errors clustered at the level of individuals. Panel B performs a refined survey test, that makes use of the repeated wave structure in the German SMS data. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Search Effort Since Start of UI Spell

	(1)	(2)	(3)	(4)
$[2,3]$ months (omitted category)	0.00	0.00	0.00	0.00
	[.]	[.]	[.]	[.]
on UI since $[3,4]$ months	2.35	0.99	-1.14	-1.23
	[1.95]	[1.91]	[1.69]	[1.72]
on UI since $[4,5]$ months	0.39	-1.29	-0.15	0.87
	[2.59]	[2.51]	[2.16]	[2.20]
on UI since $[5,6]$ months	-2.01	-3.33	-0.45	1.11
	[2.34]	[2.80]	[2.29]	[2.41]
on UI since $[6,7]$ months	1.24	-1.20	-0.08	1.67
	[3.03]	[3.18]	[2.69]	[2.83]
Adj. R^2	0.000	0.046	0.470	0.471
Mean Dep. Var	86.578	86.578	86.578	86.578
N Observations	29536	29536	29536	29536
N Individuals	2022	2022	2022	2022
Individual Controls		X		
Individual FE			X	X
Time FE				X

This table shows estimates of job-search in minutes on time on UI. Included are all job-search responses at time of nonemployment in the examined range of UI duration of individuals with $P \geq 8$. SE (in brackets) are clustered on the individual level. Controls include dummies for gender, German nationality, wave, initial eligibility and UI duration, educational groups and age in years. Time-FE control for calendar months and weekday of survey. P-Values report the H_0 of the performed test. Hypotheses are formulated such that H_1 is consistent with the ref-dependent model. *, ** and *** denote significance on 10%, 5% and 1% significance level, respectively.

Table 4: Search Effort Around UI Exhaustion

	(1)	(2)	(3)	(4)
$[-4, -3]$ months since UI exhaustion	-3.28	-7.56***	-6.62***	-7.27***
	[2.13]	[2.44]	[1.97]	[1.99]
$[-3, -2]$ months since UI exhaustion	0.11	-3.63*	-3.65**	-4.27**
	[1.92]	[2.09]	[1.81]	[1.83]
$[-2, -1]$ months since UI exhaustion	1.82	-1.91	-3.43**	-3.76**
	[1.97]	[1.90]	[1.56]	[1.56]
$[-1, 0]$ months since UI exhaustion (omitted cat.)	0.00	0.00	0.00	0.00
	[.]	[.]	[.]	[.]
$[0, 1]$ months since UI exhaustion	-0.95	-0.85	-2.07*	-1.96*
	[1.27]	[1.25]	[1.09]	[1.10]
$[1, 2]$ months since UI exhaustion	-3.45**	-2.32	-3.43**	-2.75*
	[1.67]	[1.68]	[1.48]	[1.48]
$[2, 3]$ months since UI exhaustion	-6.17***	-4.41**	-5.04***	-4.16**
	[1.97]	[1.93]	[1.65]	[1.65]
$[3, 4]$ months since UI exhaustion	-10.17***	-7.75***	-7.25***	-5.81***
	[2.34]	[2.22]	[1.85]	[1.87]
Adj. R^2	0.001	0.043	0.498	0.499
Mean Dep. Var	84.271	84.271	84.271	84.271
N Observations	89876	89876	89876	89876
N Individuals	5530	5530	5530	5530
Individual Controls		X		
Individual FE			X	X
Time FE				X

This table shows estimates of job-search in minutes on time since UI exhaustion. SE (in brackets) are clustered on the individual level. P-Values report the H_0 of the performed test. Hypotheses are formulated such that H_1 is consistent with the ref-dependent model. *, ** and *** denote significance on 10%, 5% and 1% significance level, respectively.

Table 5: Search Effort Since Start of UI Spell - Robustness

	Baseline	Full Participants	Narrow Nonemp.	Bi-weekly Level	Non resp. as zero.	Cap at 240 min	Cap at 480 min	Controlling for Local UR	Re-weighted to Match: Contacted	Re-weighted to Match: UI-Population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$[2,3]$ months (omitted category)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]
on UI since $[3,4]$ months	-1.23	-1.26	-0.71	-0.28	-2.65	-2.02	-0.58	-1.13	-0.36	-1.00
	[1.72]	[1.99]	[1.77]	[1.97]	[1.65]	[1.42]	[1.87]	[1.72]	[1.73]	[1.74]
on UI since $[4,5]$ months	0.87	1.41	1.26	1.63	-1.62	-1.29	2.29	1.16	1.32	1.80
	[2.20]	[2.50]	[2.31]	[2.60]	[2.08]	[1.80]	[2.42]	[2.22]	[2.23]	[2.35]
on UI since $[5,6]$ months	1.11	0.45	1.51	2.14	-1.08	-0.82	2.23	1.55	2.14	2.28
	[2.41]	[2.60]	[2.74]	[3.17]	[2.26]	[1.97]	[2.59]	[2.47]	[2.28]	[2.39]
on UI since $[6,7]$ months	1.67	3.08	0.77	0.90	-0.26	-1.08	2.99	2.19	3.16	3.47
	[2.83]	[3.07]	[3.44]	[4.01]	[2.68]	[2.26]	[3.09]	[2.90]	[2.71]	[2.79]
Adj. R^2	0.471	0.489	0.479	0.674	0.429	0.452	0.473	0.471	0.470	0.471
Mean Dep. Var	86.578	84.599	86.709	85.685	77.606	79.893	88.866	86.578	86.578	86.578
N Observations	29536	20618	26244	7843	32951	29536	29536	29536	29536	29536
N Individuals	2022	1047	2022	1970	2024	2022	2022	2022	2022	2022
Individual FE	X	X	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X	X	X
Monthly Local UR								X		

This table shows estimates of job-search in minutes on time since the start of the UI spell for alternative specifications, where column (1) is the baseline specification. Column (2) includes only "full participants", that are still non-employed and who still participate in the survey after 4 months since survey start. Column (3) applies a stricter non-employment definition by including only observations for which individuals report at the same or a later date to still be nonemployed. Column (4) aggregates to the bi-weekly level and repeats the baseline estimate on that level. Column (5) replaces non-responses with zeros, if for the individual at least one later actual response is observed. Column (6) and (7) change the threshold above which responses are winsorized. Column (8) controls for the county x month unemployment rate at time of survey. Column (9) and (10) re-weight observations based on a variety of observed characteristics in order to match the average characteristics observed among all contacted individuals (column (9)) and the universe of UI recipients during the time of the survey (column (10)). SE (in brackets) are clustered on the individual level. *, ** and *** denote significance on 10%, 5% and 1% significance level, respectively.

Table 6: Search Effort Around UI Exhaustion - Robustness

	Baseline	Full Participants	Narrow Nonemp.	Bi-weekly Level	Non resp. as zero.	Cap at 240 min	Cap at 480 min	Controlling for Local UR	Re-weighted to Match Contacted	UI-Population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$[-4,-3]$ months since UI exhaustion	-7.27***	-7.90***	-6.78***	-7.46***	-5.81***	-5.26***	-8.49***	-7.66***	-8.56***	-8.36***
	[1.99]	[2.14]	[2.18]	[2.23]	[2.10]	[1.64]	[2.18]	[2.02]	[2.01]	[1.99]
$[-3,-2]$ months since UI exhaustion	-4.27**	-5.91***	-4.27**	-4.04**	-3.88**	-3.03**	-5.11**	-4.55**	-5.75***	-5.20***
	[1.83]	[1.97]	[2.01]	[2.04]	[1.94]	[1.49]	[1.99]	[1.84]	[1.88]	[1.83]
$[-2,-1]$ months since UI exhaustion	-3.76**	-4.23**	-3.27*	-3.71**	-3.93**	-3.15**	-4.03**	-3.89**	-5.13***	-5.00***
	[1.56]	[1.69]	[1.73]	[1.78]	[1.70]	[1.28]	[1.70]	[1.56]	[1.64]	[1.60]
$[-1,0]$ months since UI exhaustion (omitted cat.)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]
$[0,1]$ months since UI exhaustion	-1.96*	-1.79	-1.79	-1.77	-2.81**	-2.39***	-1.80	-1.86*	-2.00*	-1.90*
	[1.10]	[1.23]	[1.24]	[1.24]	[1.20]	[0.91]	[1.19]	[1.10]	[1.14]	[1.12]
$[1,2]$ months since UI exhaustion	-2.75*	-3.88**	-1.95	-3.28**	-3.44**	-2.95**	-2.58	-2.49*	-2.38	-2.55*
	[1.48]	[1.58]	[1.67]	[1.63]	[1.59]	[1.24]	[1.61]	[1.50]	[1.57]	[1.53]
$[2,3]$ months since UI exhaustion	-4.16**	-4.59***	-3.50*	-4.25**	-5.23***	-4.09***	-3.95**	-3.76**	-3.81**	-3.79**
	[1.65]	[1.75]	[1.86]	[1.84]	[1.76]	[1.37]	[1.81]	[1.68]	[1.75]	[1.66]
$[3,4]$ months since UI exhaustion	-5.81***	-6.11***	-5.65**	-6.33***	-7.09***	-5.76***	-5.48***	-5.29***	-4.93**	-4.58**
	[1.87]	[1.96]	[2.36]	[2.08]	[2.25]	[1.59]	[2.01]	[1.90]	[1.99]	[1.90]
Adj. R^2	0.499	0.513	0.505	0.669	0.455	0.480	0.501	0.499	0.489	0.497
Mean Dep. Var	84.271	81.893	84.313	83.945	75.035	77.613	86.706	87.732	84.271	84.271
N Observations	89876	65472	77847	27200	87472	89876	89876	89876	89876	89876
N Individuals	5530	3126	5342	5400	5345	5530	5530	5530	5530	5530
Individual FE	X	X	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X	X	X
Monthly Local UR								X		

This table shows estimates of job-search in minutes on time since UI exhaustion for alternative specifications, where column (1) is the baseline specification. Column (2) includes only "full participants", that are still non-employed and who still participate in the survey after 4 months since survey start. Column (3) applies a stricter non-employment definition by including only observations for which individuals report at the same or a later date to still be nonemployed. Column (4) aggregates to the bi-weekly level and repeats the baseline estimate on that level. Column (5) replaces non-responses with zeros, if for the individual at least one later actual response is observed. Column (6) and (7) change the threshold above which responses are winsorized. Column (8) controls for the county x month unemployment rate at time of survey. Column (9) and (10) re-weight observations based on a variety of observed characteristics in order to match the average characteristics observed among all contacted individuals (column (9)) and the universe of UI recipients during the time of the survey (column (10)). SE (in brackets) are clustered on the individual level. *, ** and *** denote significance on 10%, 5% and 1% significance level, respectively.

Table 7: Structural Estimates of Job Search Models

	(1)	(2)	(3)	(4)	(5)	(6)
		δ-discounting			$\beta\delta$-discounting	
	Standard 3 type	Ref. Dep. 2 type	Ref. Dep. 3 type	Standard 3 type	Ref. Dep. 2 type	Ref. Dep. 3 type
Parameters of Utility Function						
Loss aversion λ	.	5.96	12.6	.	3.18	2.66
		[0.68]	[1.97]		[1.32]	[0.63]
Adjustment speed of ref. point N	.	403.7	451.3	.	297.9	338.4
		[27.8]	[32.7]		[22.7]	[32.6]
Discount factor (30 days) δ	0.639	0.931	0.915	0.995	0.995	0.995
	[0.0658]	[0.00876]	[0.0184]	[0]	[0]	[0]
Discount factor β	1	1	1	0.918	0.475	0.473
	[0]	[0]	[0]	[0.00874]	[0.127]	[0.0943]
Parameters of Search Cost and Productivity						
Curvature of search cost γ	18.7	3.16	5.58	1.88	4.59	1.68
	[0.42]	[0.031]	[0.058]	[0.068]	[1.39]	[0.26]
Curvature of search effort productivity ζ	8.21	1.65	3.06	1.51	1.77	0.39
	[0.20]	[0.010]	[0.021]	[0.061]	[0.62]	[0.061]
Composite curvature $\widetilde{\gamma} = \frac{\gamma-\zeta}{1+\zeta}$	1.13	0.57	0.62	0.15	1.02	0.93
Search Cost for Type 1 (ln(k1))	-56.3	-17.0	-26.7	-3.96	-23.9	-7.71
	[233.6]	[0.12]	[9.13]		[6.12]	[3.88]
Type 1 (ln(E1))	-25.5	-14.0	-18.4	-24.7	-14.8	-5.02
	[109.5]	[0.060]	[5.64]	[0.28]	[2.53]	[2.18]
Search Cost for Type 2 (ln(k2))	-86.7	-17.4	-26.7	-6.57	-25.3	-12.3
	[49.7]	[0.28]	[0.48]	[0.17]	[6.10]	[1.64]
Type 1 (ln(E2))	-41.8	-12.9	-19.8	-8.81	-13.2	-9.80
	[23.3]	[0.15]	[0.31]	[0.13]	[2.56]	[0.31]
Search Cost for Type 3 (ln(k3))	-94.9	.	-58.7	-12.9	.	-30.3
	[16.3]		[93.4]	[0.36]		[15.0]
Type 1 (ln(E3))	-44.0	.	-36.9	-12.8	.	-15.2
	[7.66]		[57.5]	[0.32]		[7.60]
Share of Highest Cost Type p1	0.17	0.49	0.50	0.24	0.44	0.58
	[0.11]	[0.013]	[0.027]	[0.012]	[0.026]	[0.025]
Share of Highest Cost Type p2	0.37	.	0.49	0.31	.	0.41
	[0.021]		[0.029]	[0.014]		[0.026]
Model Fit						
Number of Moments Used	49	49	49	49	49	49
Number of Estimated Parameters	11	10	13	11	10	13
SSE for Hazard	127.4	156.6	118.8	91.2	117.6	92.1
SSE for Inital Effort	14.2	17.2	17.4	14.2	28.4	13.4
SSE for Effort around Exhaustion	139.8	33.9	30.8	144.2	40.5	23.7
Goodness of Fit (SSE)	281.6	208.4	167.0	249.6	186.9	129.2

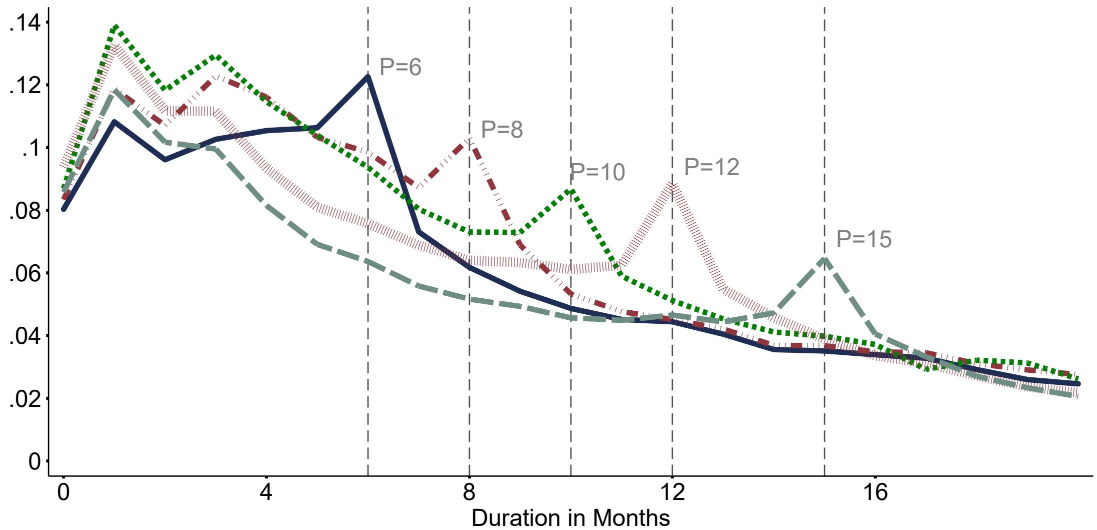
Notes: The table shows parameter estimates for the standard and the reference-dependent search models. Estimation is based on minimum distance estimation. The targeted moments are 1) the within-person estimates of the evolution of search effort at the beginning of the spell, 2)the evolution of effort at UI exhaustion, and 3) the empirical hazards for the P=8 and P=10 month groups, that are estimated using a regression discontinuity design at the cutoff, to keep the composition between the two groups identical. Standard errors for estimated parameters in parentheses.

Table 8: Robustness Table for Structural Estimation

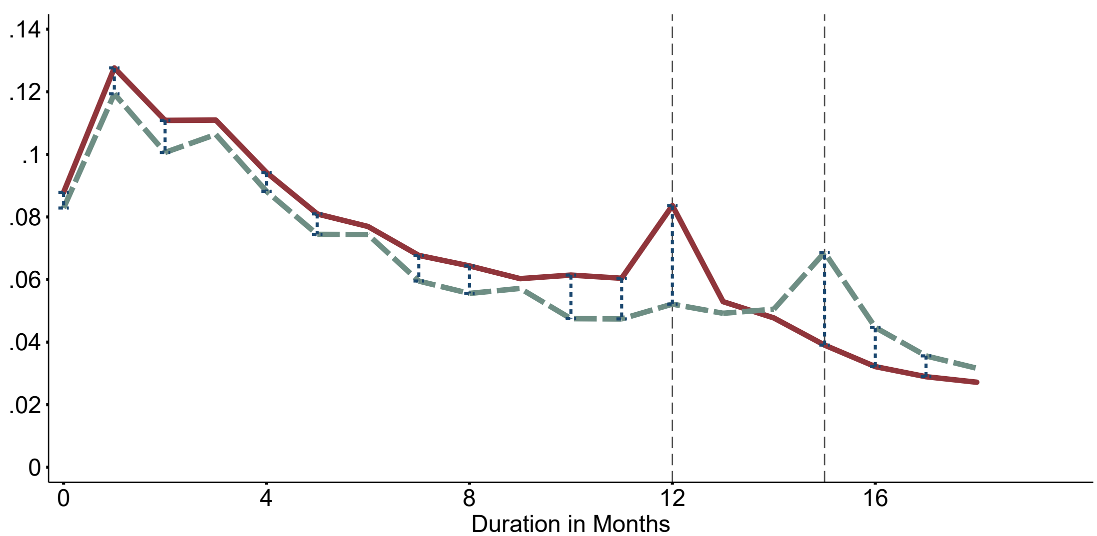
	(1) Estimate β and δ	(2) Estimate η	(3) Estimate η; fix λ	(4) Pos. initial Assets	(5) Effort upweighted $\times$ 1	(6) No Decline FE	(7) Estimate using P=8/10 Group
Standard Model - 3 Types							
Discount factor (30 days) δ	0.911	0.995	0.995	0.995	0.995	0.995	0.995
	[0.123]	[0]	[0]	[0]	[0]	[0]	[0]
Discount factor β	0.646	0.919	0.918	0.484	0.920	0.917	0.717
	[0.0188]	[0.00865]	[0.00874]	[0.0258]	[0.0203]	[0.0109]	[0.0307]
Curvature of search cost γ	10.1	1.88	1.88	8.42	1.88	3.45	3.40
	[0.12]	[0.065]	[0.068]	[0.077]	[0.068]	[0.026]	[0.24]
Curvature of search effort productivity ζ	5.65	1.51	1.51	4.62	1.52	2.88	1.80
	[0.059]	[0.059]	[0.061]	[0.070]	[0.057]	[0.027]	[0.16]
Composite curvature $\widetilde{\gamma}=\frac{\gamma-\zeta}{1+\zeta}$	0.68	0.15	0.15	0.68	0.14	0.15	0.57
Number of Moments Used	49	49	49	49	49	45	49
Number of Estimated Parameters	12	11	11	11	11	11	11
SSE for Hazard	105.2	91.2	91.2	127.6	90.9	90.9	194.5
SSE for Inital Effort	12.6	14.1	14.2	13.0	1.42	12.6	13.7
SSE for Effort around Exhaustion	131.3	144.3	144.2	125.7	14.5	168.4	132.4
Goodness of Fit (SSE)	249.1	249.6	249.6	266.4	106.8	118.8	340.6
Reference Dependent Model - 3 Types							
Loss aversion λ	2.81	1.28	1	4.92	5.70	0.95	3.88
	[1.29]	[1.12]	[0]	[0.80]	[0.60]	[0.056]	[1.18]
Eta	1	4.24	3.35	1	1	1	1
		[0.13]	[1.76]				
Adjustment speed of ref. point N	330.4	357.2	66.0	306.3	412.1	76.8	568.8
	[54.6]	[44.3]	[2.81]	[28.1]	[12.3]	[6.23]	[62.1]
Discount factor (30 days) δ	0.967	0.995	0.995	0.995	0.995	0.995	0.995
	[0.111]	[0]	[0]	[0]	[0]	[0]	[0]
Discount factor β	0.475	0.473	0.511	0.350	0.896	0.821	0.763
	[0.0477]	[0.123]	[0.204]	[0.0403]	[0.00786]	[0.0689]	[0.0230]
Curvature of search cost γ	3.26	2.46	8.17	3.06	1.92	3.02	3.01
	[1.92]	[0.34]	[7.99]	[0.022]	[0.0099]	[1.95]	[0.045]
Curvature of search effort productivity ζ	1.12	0.75	4.02	0.76	1.38	2.11	1.74
	[0.89]	[0.030]	[4.32]	[0.0099]	[0.0088]	[1.48]	[0.019]
Composite curvature $\widetilde{\gamma}=\frac{\gamma-\zeta}{1+\zeta}$	1.01	0.98	0.83	1.30	0.23	0.29	0.47
Number of Moments Used	49	49	49	49	49	45	49
Number of Estimated Parameters	14	14	13	13	13	13	13
SSE for Hazard	93.0	87.6	65.8	86.7	62.6	52.4	137.2
SSE for Inital Effort	12.8	12.5	9.36	20.9	2.75	6.84	23.1
SSE for Effort around Exhaustion	23.2	23.2	65.4	25.4	4.39	160.8	36.7
Goodness of Fit (SSE)	129.0	123.4	140.7	133.0	69.7	76.4	197.0

Notes: The table shows parameter estimates for the standard and the reference-dependent search models. Estimation is based on minimum distance estimation. The targeted moments are 1) the within-person estimates of the evolution of search effort at the beginning of the spell, 2)the evolution of effort at UI exhaustion, and 3) the empirical hazards for the P=8 and P=10 month groups, that are estimated using a regression discontinuity design at the cutoff, to keep the composition between the two groups identical. Standard errors for estimated parameters in parentheses. [.] indicates that the parameter estimate is on the boundary and thus the standard error is not well identified.

Figure 1: Re-employment Hazard Using Administrative Data



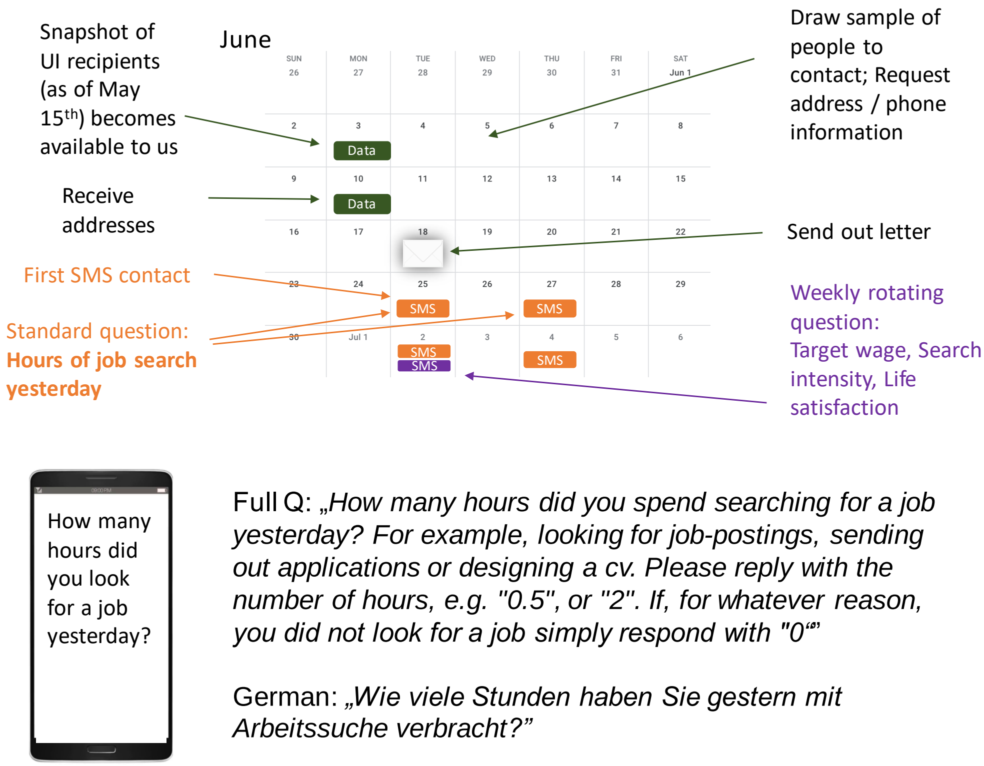
(a) All Eligibility Categories



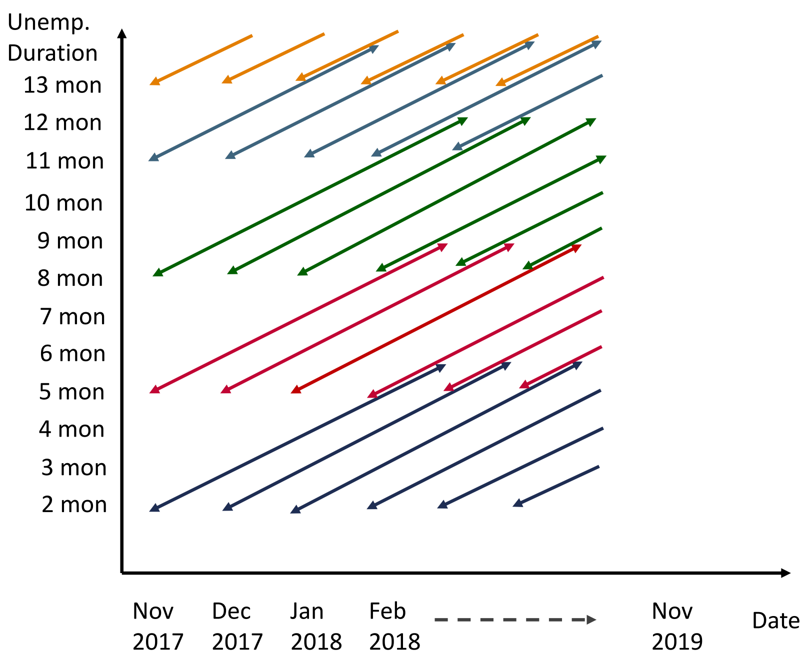
(b) Regression Discontinuity at Age 50

Notes: This figure shows reemployment hazards by PBD groups based on administrative data between January 2013 and June 2016. Panel (a) shows hazard rates for all 5 PBD-groups, whereas figure (b) provides RD-estimates of the 12 vs. 15 month eligibility group around the discontinuity at age 50. The sample consists of individuals aged between 28 and 60 at time of UI entry and have exactly 6, 8, 10, 12 or 15 months of PBD at UI entry. For PBD=12 and PBD=15, we additionally restrict to age between 45 and 55 at time of UI entry and on qualifying for long UI eligibility based on working history. We also restrict to immediate UI take-up after job-loss (<2 days). Numbers of observations for panel are for P=6: 113568, for P=8: 80809, for P=10: 59967, for P=12: 258954 and for P=15: 216307.

Figure 2: Survey Design



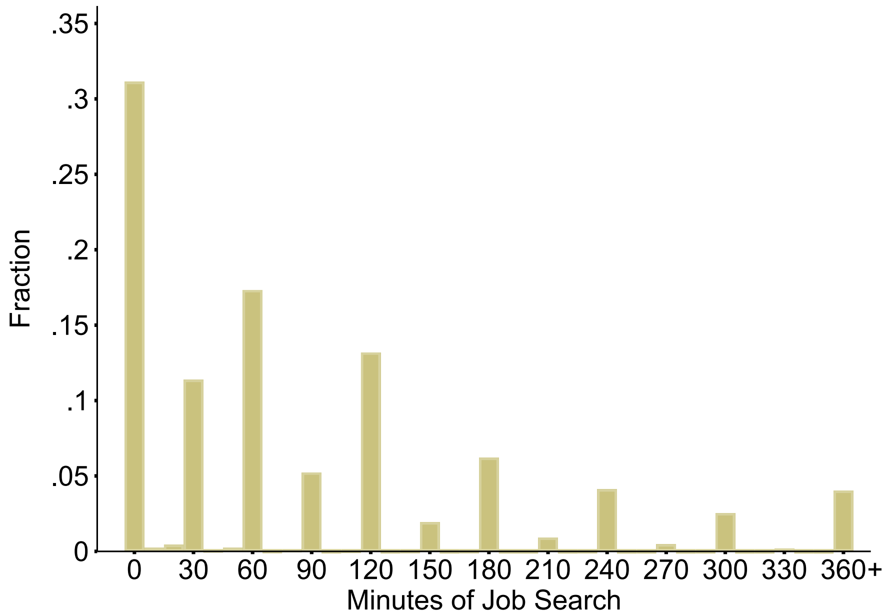
(a) Timing of Sampling and Survey Design



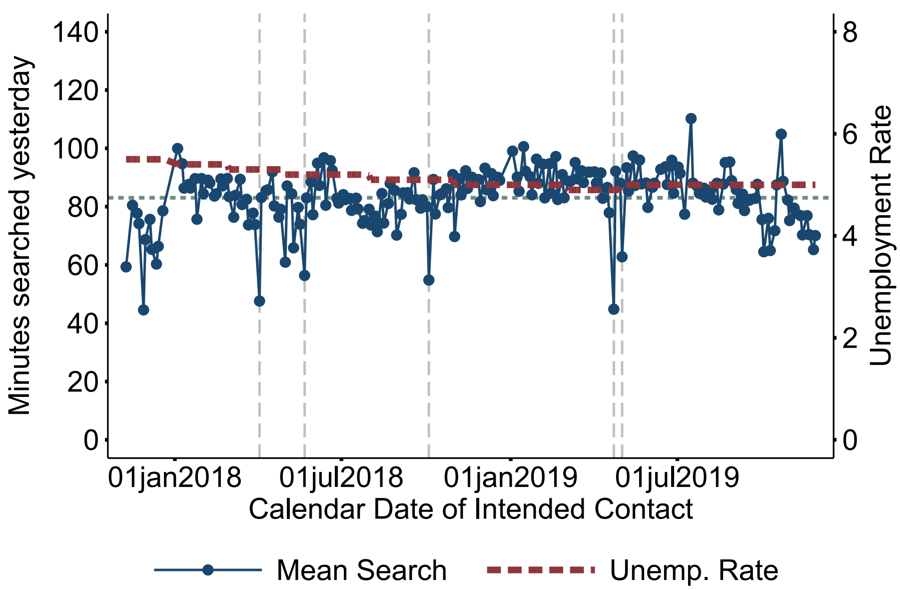
(b) Overlapping Panel Design for P=12 Group

Notes: This figure illustrates (a) the overlapping cohort structure by wave, and (b) timing of data retrieval, send out of letter and first SMS contact.

Figure 3: Distribution and Time Series of Job Search Measure



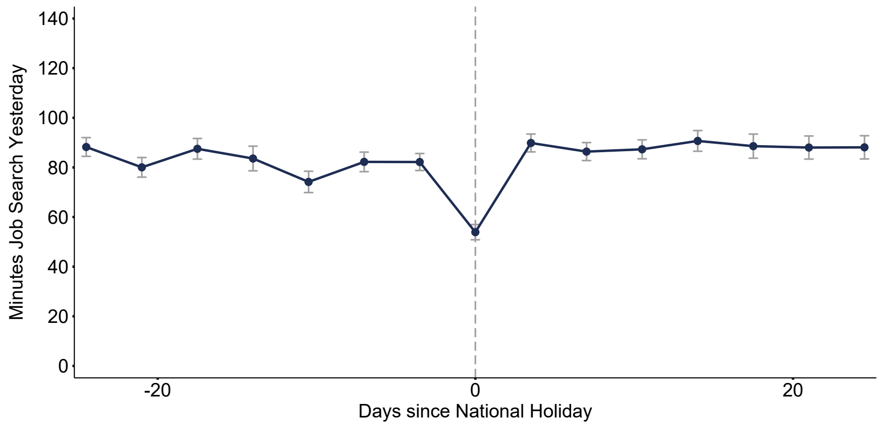
(a) Histogram of Job Search Responses



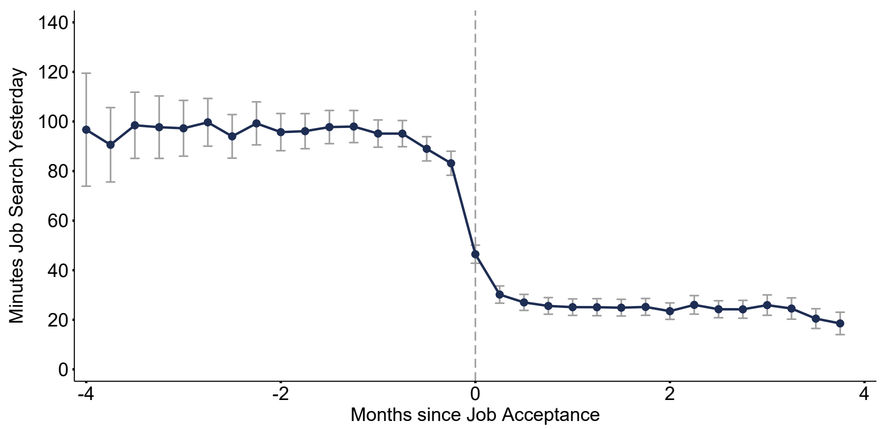
(b) Time Series of Job Search and Unemployment Rates

Notes: Panel (a) shows a histogram for job-search for all responses for individuals who still report being nonemployed. We drop responses above 15 hours and censor responses to 6 hours. Panel (b) shows time series of mean daily search (of nonemployed job searchers) for days with at least 20 valid responses. The horizontal dashed line indicates the mean job search over the whole period, the vertical dashed lines indicate days of federal public holidays. The red dashed line shows the seasonally adjusted monthly unemployment rate.

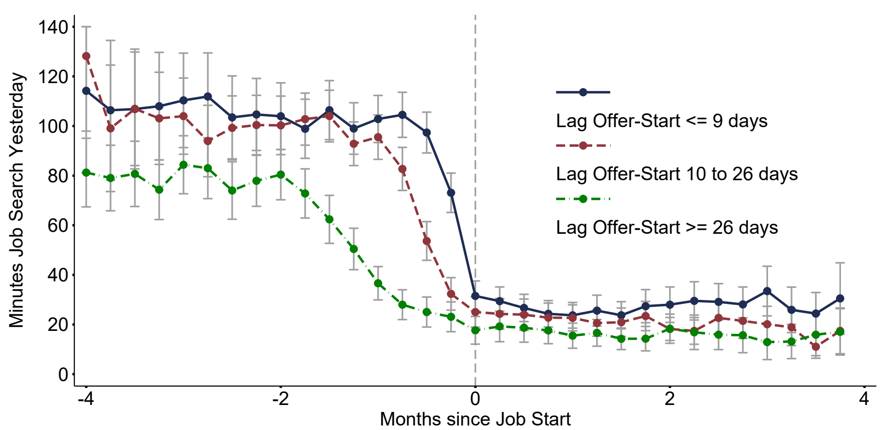
Figure 4: Validation of Search Effort Measure



(a) Search Effort Around National Holidays



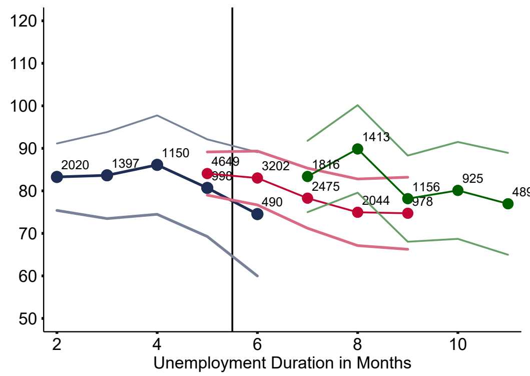
(b) Search Effort Around Job Acceptance



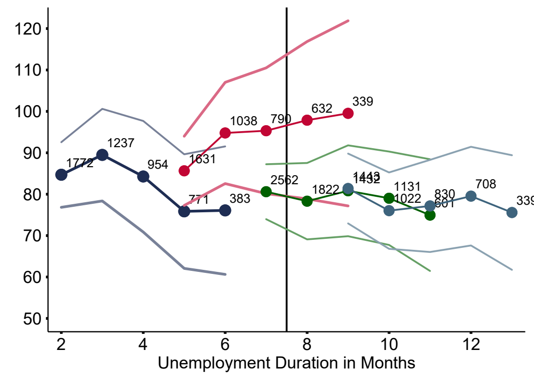
(c) Search Effort Around Job Start, by time since Acceptance

Notes: This figure shows mean job search effort for nonemployed individuals around different events. Event dates are normalized to zero. In figure (c) the distance between two survey dates (Tuesday $->$ Thursday and Thursday $->$ Tuesday) is standardized to 3.5 days for the ease of comparison.

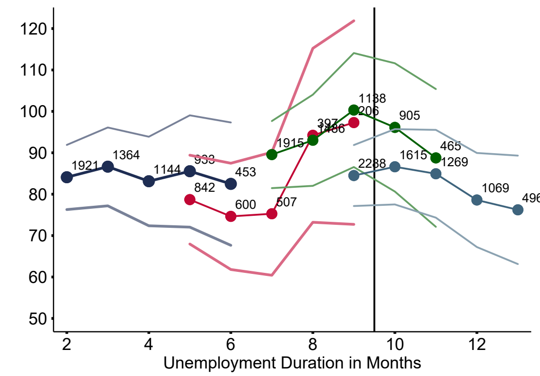
Figure 5: Search Effort (Minutes of Job-Search Yesterday) over the Unemployment Spell by Survey Cohort



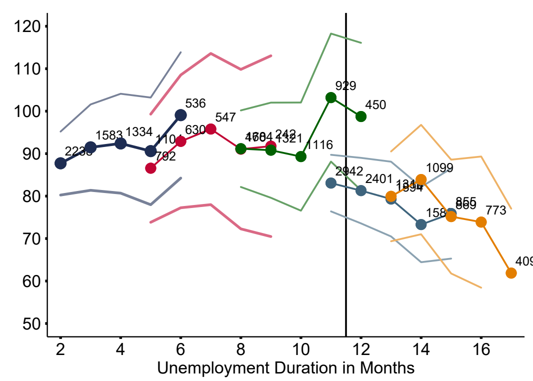
(a) P=6 Months Group



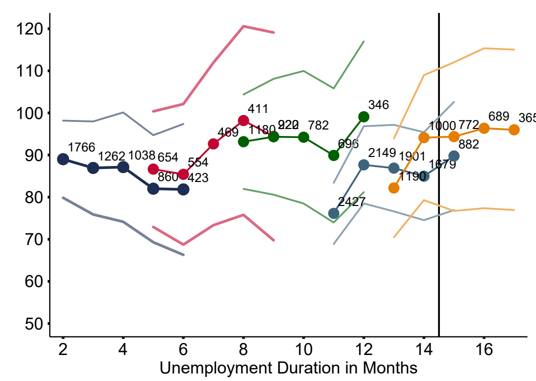
(b) P=8 Months Group



(c) P=10 Months Group



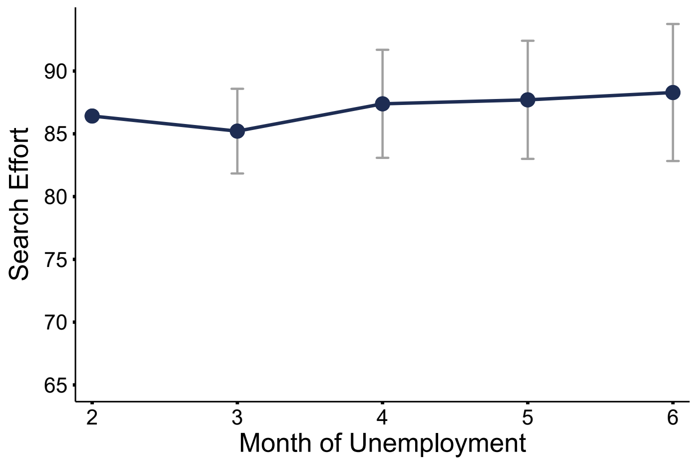
(d) P=12 Months Group



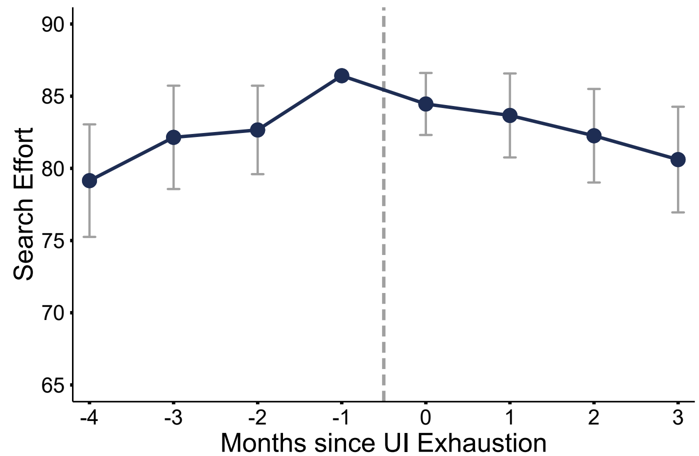
(e) P=15 Months Group

Notes: This figure shows cohort plots for P=6 to P=15 months. 95% CI (SE clustered on individual level) are displayed as outer lines (values above 125 and below 50 are censored for the ease of exposition). Numbers at a dot refer to the numbers of observations on which the dot is based. A cohort is defined as the duration in months on UI at time of first contact. It contains the months 2,3,5,8,11,13. Values that are -due to slight differences in definition of cohorts in earlier waves- outside those range are increased by one months such that they are fit in the listed month range. One dot represents observations from 4 weeks. Since responses are restricted to the regular survey duration (up to 18 weeks), the last dot of each cohort contains only observations from two weeks.

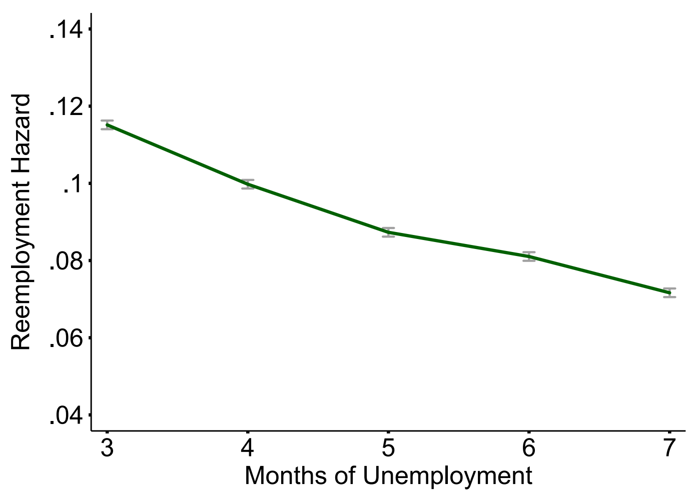
Figure 6: Search Effort Throughout the Unemployment Spell



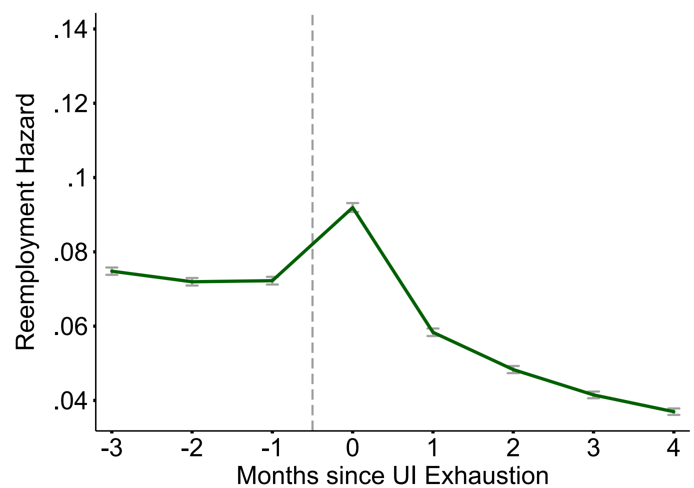
(a) Initial Evolution of Search Effort (N ind. = 2022, N obs. = 29536)



(b) Search Effort around UI Exhaustion (N ind. = 5530, N obs. = 89876)



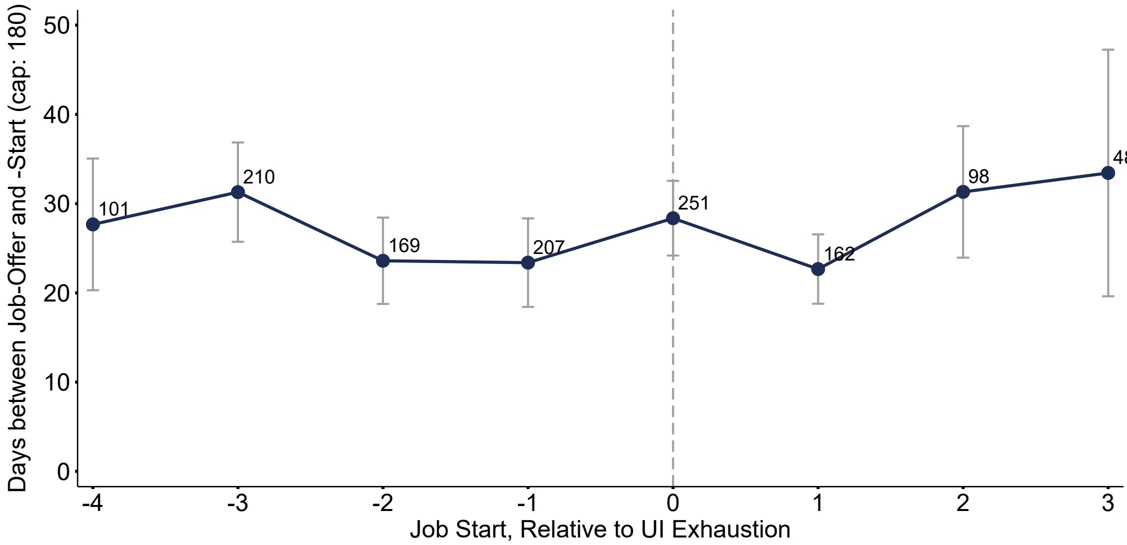
(c) Initial Evolution of Hazard Rate



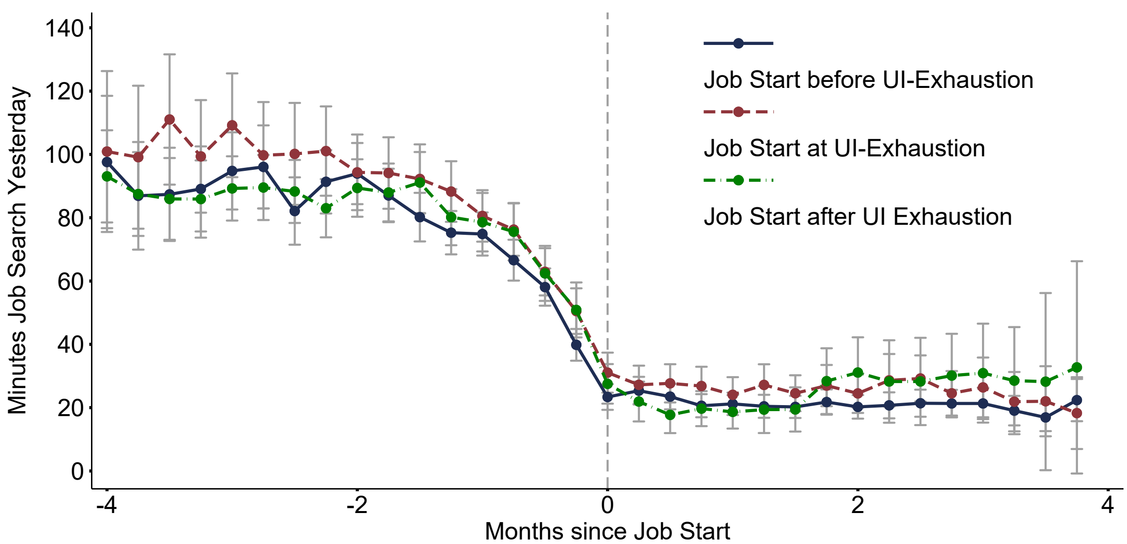
(d) Hazard Rate around UI Exhaustion

Notes: The figure shows mean job search over the initial spell of unemployment (up to 6 months) and around UI-exhaustion (between -4 and +3 months around UI exhaustion) controlling for individual, weekdate and calender-month fixed effects and compares it to reemployment hazard in those months. For the initial evolution of Search Effort only individuals with $P \geq 8$ are included. Standard Errors are clustered on the Person level. Hazard rates are pooled over different P-groups where each group is weighted with the number of individuals that are in the respective survey group.

Figure 7: Evidence about Storable Offer Model



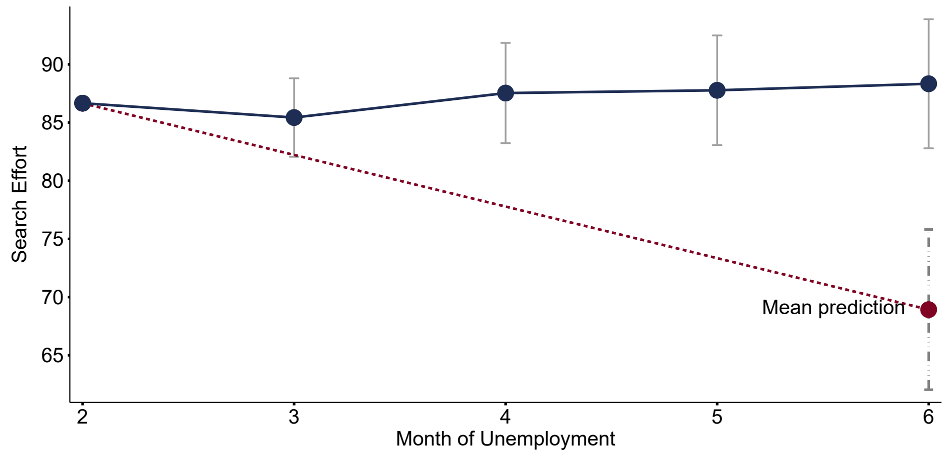
(a) Mean Duration between Job-Offer and Job-Found by Date of UI Exhaustion



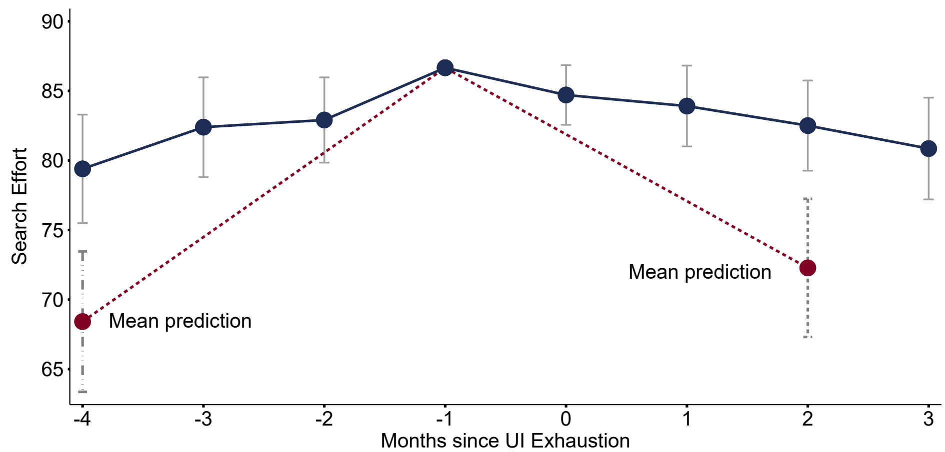
(b) Job Search Effort by Job Found and Date of UI Exhaustion

Notes: Panel (a) shows the duration in days between job-offer and job start by the month of the job start relative to UI exhaustion. Panel (b) shows reported job search intensity around job start by whether individuals start their job around UI exhaustion (+/- one month around UI exhaustion) or at other points of their unemployment spell.

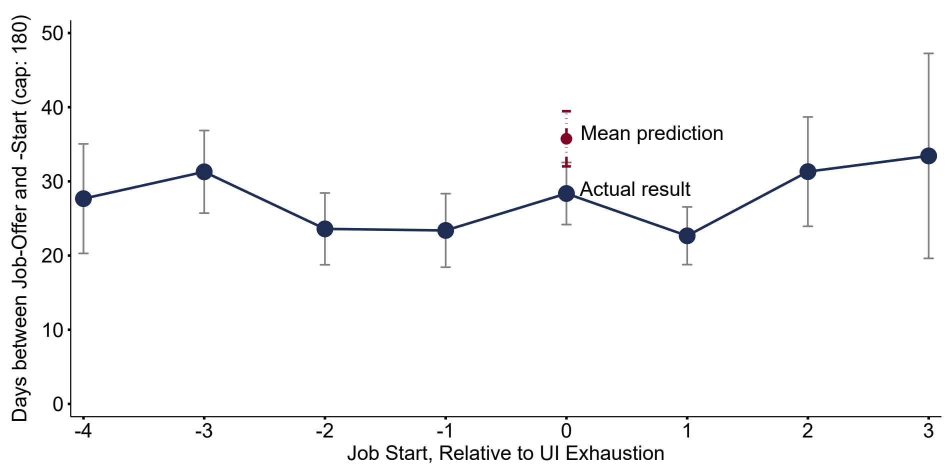
Figure 8: Expert Forecasts vs. Survey Results



(a) Search Effort Early In Spell



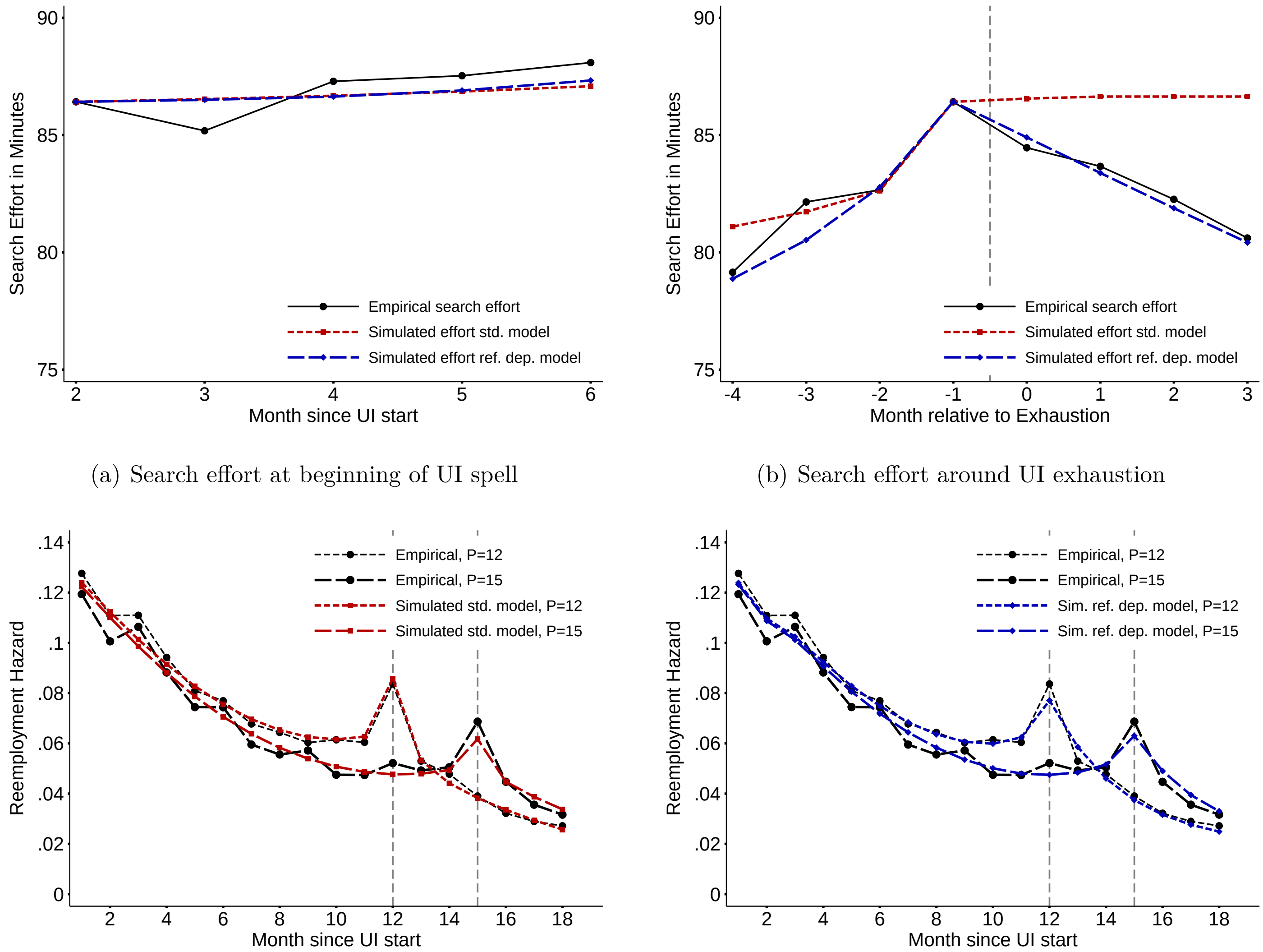
(b) Search Effort Around UI Exhaustion



(c) Evidence of Storable Offers Around UI Exhaustion

Notes: This figure contrasts the expert forecasts with the results of the survey for the three main findings.

Figure 9: Predicted Moments of the Standard and Reference-Dependent Models - Present Bias ($\beta\delta$)



(a) Search effort at beginning of UI spell

(b) Search effort around UI exhaustion

(c) Hazard rate for standard model

(d) Hazard rate for ref.-dep. model

Notes: The figure shows the empirical moments that we use in the structural estimation and the predicted moments from the estimated standard and reference-dependent models. The standard model corresponds to Table 7, Column (4), while the reference-dependent model corresponds to Table 7, Column (6).