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DISCUSSION PAPER SERIES

IZA DP No. 17839

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ABSTRACT

Deter and Deteriorate: The Effects of Application Processing Times on Welfare Receipt and Employment*

This paper investigates the effects of application processing times on welfare applicants' benefit and employment outcomes. For causal inference, we exploit exogenous variation in application processing times stemming from the random assignment of caseworkers. Our findings indicate that longer application processing times deter applicants from receiving benefits, particularly those with better labor market prospects. In contrast, for applicants who eventually receive benefits, longer processing times reduce labor market attachment and increase benefit dependency. Finally, using exogenous variation in caseworkers' provision of benefit prepayments, we find that the receipt of welfare prepayments increases the employment and earnings of awarded applicants. This suggests that reduced financial stress improves successful job search.

JEL Classification: D73, H53, I38

Keywords: welfare benefits, program application, processing times, benefit prepayments, instrumental variables

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1 Introduction

Effective targeting of benefits is essential for achieving the core objectives of social insurance, namely income support and resource allocation. Eligibility checks, typically conducted by caseworkers, play a crucial role in the screening of benefit applications. An often overlooked aspect of this process is that screening takes time, potentially extending the period between application submission and benefit award decision. This delay imposes implicit costs on applicants, which may not only affect their decision to complete the application process but also their post-application outcomes. Longer application times are therefore associated with higher formal and informal costs inherent with the take-up of benefits (Currie, 2006; Ko & Moffitt, 2024).

This paper investigates the causal effects of application processing times on welfare applicants' subsequent benefit and labor market outcomes. Our study uses administrative data from the Netherlands, where welfare benefits serve as a last resort for unemployed individuals. As part of the application process, welfare applicants must provide caseworkers with detailed information about their living conditions, income, and assets. Caseworkers assess eligibility and may request additional personal information. As caseworkers vary substantially in the speed at which they collect and assess this information, application processing times partially depend on the randomly assigned caseworker. Furthermore, to mitigate financial hardship due to long processing times, applicants may receive provisional benefit prepayments four weeks after submitting their benefit application.

We argue that longer processing times affect outcomes through two potential mechanisms: a discouragement effect ("deterrence") and reduced labor attachment while waiting ("deterioration"). These mechanisms have opposing effects on benefit receipt and employment outcomes, making the overall effect of application processing times ambiguous. The first mechanism is that longer processing times can reduce welfare benefit take-up and increase employment.[1] This effect may be largely

[1] In this study, we are interested in the effects of variation in processing times that are ex ante *unknown* to the applicants. This distinction from ex ante *known* differences in application duration is important as the latter can deter potential applicants from applying (see for example Autor et al., 2014; Bolhaar et al., 2019; Storer & Van Audenrode, 1995). Our analysis does not

mechanical, as some applicants will secure employment while awaiting the award decision. Prolonged uncertainty may also prompt applicants to increase job search efforts, accept lower wages, and withdraw their application as the application process continues to lengthen.

The second mechanism is that longer processing times themselves may directly reduce applicants' subsequent employment and earnings outcomes (Parsons, 1991). Longer processing times postpone entry into the welfare program, potentially resulting in longer periods of inactivity during which applicants await the award decision. This delay may adversely affect the applicants' employment and earnings potential. During the application process, applicants' job search efforts are often not monitored, and reintegration services have yet to begin. Applicants may also wrongfully assume that resuming work would result in the loss of any accumulated welfare benefits. Prolonged application periods can further weaken labor market attachment due to increased financial stress (Ridley et al., 2020; Kaur et al., 2025) and the negative signal that prolonged unemployment may send to employers regarding productivity (Kroft et al., 2013).

For the empirical analysis, we use welfare application data from the second-largest city in the Netherlands (Rotterdam) combined with socio-demographic administrative records from Statistics Netherlands. We observe considerable variation in the application processing times, with an average processing time of 9 weeks and a standard deviation of 3.1 weeks in our sample. This variation is partially driven by differences in processing speed among caseworkers, who act as adjudicators. To estimate the causal effects of longer application processing times, we exploit this variation and the random assignment of applications to these caseworkers.[2] Our key identifying assumption is that the processing speed of caseworkers is orthogonal to other relevant dimensions on which the caseworkers might differ, such as the award rate. This assumption can be justified by: (i) unambiguous eligibility rules leave no discretionary room for the caseworkers on the benefit award decisions; (ii)

shed light on this channel.

[2]Our instrumental variable approach is inspired by an increasing number of studies exploiting judge or caseworker stringency as an instrumental variable (e.g. Aizer & Doyle Jr, 2015; Arni & Schiprowski, 2019; Bhuller et al., 2020; Doyle Jr, 2007, 2008; Kling, 2006; Maestas et al., 2013).

caseworkers are not involved in the monitoring of job search requirements or reintegration activities; and (iii) caseworkers involved with claim assessments are rarely in direct contact with applicants.

Exploiting the exogenous variation in processing times from randomly assigned caseworkers, we find that longer processing times have little to no effect on *average* welfare receipt and employment outcomes. We then examine the distinct roles of deterrence and deterioration. First, regarding deterrence, the results indicate that applicants assigned to a caseworker who takes, on average, one additional week to review an application experience a 0.62 percentage points decrease in benefit take-up due to application withdrawal. This effect is particularly pronounced among welfare applicants with stronger labor market prospects. The effect is economically meaningful, considering that in total only 6 percent of applicants withdraw their application or are not awarded benefits. Second, regarding deterioration, the results show that longer application processing times increase welfare dependency and decrease the time in employment and earnings for individuals who are awarded benefits. Specifically, each additional week of processing extends welfare receipt by 0.44 weeks and reduces employment by 0.36 weeks in the first two years after application.

Finally, we delve deeper into the potential role of liquidity constraints as a driver of deterrence and deterioration effects of application waiting times, using variation in the prepayment grant rate among caseworkers.[3] We find that the receipt of welfare prepayments increases the employment and earnings of awarded applicants. This supports the idea that prepayments reduce financial stress, thereby fostering successful job search.

Our paper contributes to three strands of literature. First, we contribute to studies on the relationship between unemployment duration and subsequent labor market outcomes.[4] Our paper is most closely related to the work of Autor et al. (2015), who show that longer Social Security Disability Insurance (SSDI) application

[3]Recall that welfare benefits in the Netherlands function as a safety net and are means-tested. As a result, it is likely that many applicants are liquidity-constrained at the moment of application. Moreover, the median wealth of households receiving welfare benefits in the Netherlands in this period was between 0 and 500 euros (Statistics Netherlands, 2024).

[4]E.g. Autor et al. (2015); Davis & Von Wachter (2011); Fasani et al. (2021); Kroft et al. (2013); Marbach et al. (2018).

processing times reduce subsequent employment and earnings. Their study considers a disability insurance program, where applicants face substantial processing times (on average 61 weeks) with strong non-work incentives, leading to extended periods out of the labor force without any form of income. In contrast, our study examines a minimum income support program, with considerably shorter processing times (on average 9 weeks), where applicants are subject to job search requirements and often receive provisional benefit prepayments to offset the income delays stemming from longer applications. Despite these difference, our findings are largely consistent with the findings by Autor et al. (2015), as we also find that longer processing times lead to substantial increases of benefit receipt and reductions of employment and earnings.

Second, we contribute more broadly to the literature on the take-up and targeting of social security programs. Previous research has shown that both formal and informal costs associated with the take-up of these programs can effectively deter unemployed workers from applying (see Currie, 2006; Ko & Moffitt, 2024, for comprehensive reviews of the social benefits take-up literature). These deterrence effects may either lead to better targeting by encouraging self-screening among workers with better characteristics (Nichols & Zeckhauser, 1982; Kleven & Kopczuk, 2011), or worsen targeting by increasing non-take-up of benefits among individuals with greater need.[5] While previous research has explored factors such as benefit gains, administrative barriers, and stigma in relation to the take-up of minimum income support programs, to the best of our knowledge, we are the first to investigate the effects of processing times on the take-up of a minimum income support program that serves as a last resort for unemployed individuals lacking sufficient means to meet their basic needs.[6]

Finally, our paper contributes to studies on the adverse effects of liquidity constraints on economic outcomes. Economic theory typically predicts that wealth negatively impacts job search, as individuals with greater wealth have less urgency

[5] E.g. Deshpande & Li (2019); Finkelstein & Notowidigdo (2019); Currie (2006); Ko & Moffitt (2024).

[6] Since longer processing times in our setting partially originate from administrative burdens and program complexity, our paper also relates to the literature on the complexity of social programs (e.g. Kleven & Kopczuk, 2011; Currie, 2006; Ko & Moffitt, 2024).

to find employment (Mortensen, 1986; Blundell et al., 1997). Empirical evidence supports this, showing that liquidity-constrained unemployed workers tend to find jobs more quickly.[7] However, a growing body of research emphasizes the harmful impact of financial stress – often induced by liquidity constraints – on (mental) health and labor market outcomes.[8] To our knowledge, our study is the first to empirically examine the effects of benefit prepayments, which can alleviate financial stress for individuals awaiting a benefit award decision. In line with earlier work in this field of research, we find positive labor income effects of provisional benefit prepayments.

The remainder of the paper is organized as follows. In the next section we describe the Dutch welfare system, the application process, the availability of benefit prepayments, and the expected effects of longer processing times as well as benefit prepayments. Section 3 contains a description of the data. In Section 4 we provide our empirical framework to estimate the effects of longer processing times. Additionally, we validate the use of caseworker speed as an instrumental variable. Section 5 presents the results of the analysis in which we distinguish between the roles of deterrence and deterioration. We also investigate the effects of provisional benefit prepayments, before Section 6 concludes.

2 Institutional background

2.1 Welfare benefits in the Netherlands

In the Netherlands, welfare benefits function as a safety net for all unemployed individuals with insufficient means of subsistence. To be eligible for welfare benefits one should have insufficient earnings, possess no substantial assets, have no substantial partner income, and not or no longer be entitled to other social security benefits (such as unemployment insurance (UI) or disability insurance benefits).[9] With 22

[7]See Basten et al. (2014); Card et al. (2007); Chetty (2008).

[8]E.g. Dobbie & Song (2015, 2020); Gathergood (2012); Kaur et al. (2025); Marks et al. (2024); Ridley et al. (2020); Sergeyev et al. (2024).

[9]For applicants younger than 27 there are different rules for both the application and while receiving welfare benefits. So are younger applicants subject to a so-called 'job-search-period'. For more information on the different rules for welfare recipients aged 18 to 26 see e.g., Cammeraat

percent of welfare applicants having exhausted their UI benefits, the majority of the inflow consists of individuals with insufficient work history for UI entitlement. In addition to meeting income and asset conditions, individuals should make sufficient job search efforts.[10] Non-compliance could be sanctioned with temporary benefit reductions or benefit suspensions.

Welfare benefits in 2019 were 1,026 euros per month for single individuals (both with and without children) and 1,465 euros for couples. Additionally, households may receive housing, child, and health insurance subsidies, which are not observed in our data. With benefits amounting to about 60 percent of the median disposable income, the Dutch welfare benefits system can be considered generous compared to most other OECD countries (OECD, 2018). Individuals continue to receive welfare benefits until they find employment or reach the legal retirement age. In the first six months, welfare recipients are not subject to benefit reductions equivalent to 25 percent of their monthly earnings, up to a threshold of approximately 200 euros. Any additional income earned above this threshold leads to a reduction in welfare benefits of an equal amount.

2.2 The application process

In our analysis we use data from Rotterdam, which is the second-largest city and the city with the highest welfare benefits dependence in the Netherlands. Welfare benefit applications are assigned to caseworkers who have 8 weeks to review the application in order to determine eligibility and, if relevant, the level of benefits. The reviewing process can be characterized as back-office work, as caseworker rarely have direct contact with the applicants. The formal application period can be extended (multiple times) by the caseworker if the applicant does not provide all necessary information, for instance on income transactions (bank statements, pay slip, other benefits, tax return and alimony), residence (rent and fellow residents),

et al. (2022) and Stam et al. (2020). Similarly, for older applicants there are several differences in eligibility rules and search requirements. The first relevant age threshold for older applicants is at the age of 50 when partially disabled workers can supplement their (labor) income with welfare benefits up till the level of welfare benefits.

[10] An exemption from those search requirements can be requested by parents with full custody over children younger than five and those who are deemed fully and permanently disabled.

assets (savings, valuables and debts), a job seeker statement, and income and/or a job seeker statement of their partner, if relevant. Based on interviews with caseworkers, especially applicants' wealth and living situation can be unclear. In these cases, caseworkers can request additional information from the applicant before the application will be assessed.

If the information provided by the applicant is complete, eligibility rules for welfare are unambiguous. Consequently, caseworkers have very little room for discretion in the award decision.[11] However, caseworkers differ in processing speed and in the frequency of calls for additional information of applicants. In case the applicant is deemed eligible, the benefits will be paid retroactively from the moment of the initial application.[12] Longer processing times, however, might result in less (experienced) monitoring of job search requirements and less welfare to work services.

In the city of Rotterdam, caseworkers who assess welfare applications are not involved in monitoring of ongoing benefit conditions and in providing welfare-to-work services. Caseworkers involved with claim assessment are so-called 'income caseworkers' (in Dutch: 'inkomensconsulent'; hereafter: caseworkers), whereas those involved with return to work are 'reintegration caseworkers' (in Dutch: 'werkcoach'). The assignment of welfare applications to caseworkers is based on the current caseload of the caseworkers. More or less difficult cases are (therefore) randomly assigned. As an exception to this, some (less experienced) caseworkers assess more applications from applicants who exhausted UI benefits before applying for welfare benefits. These applications require less application time and effort from the caseworker, since the source and level of previous income is known.[13]

[11] That caseworkers have negligible discretionary leeway regarding the award decision is confirmed in interviews with caseworkers.

[12] Applicants who secure employment prior to the benefit award decision may still complete their application to claim benefits for the period between the initial application and the start of the new job.

[13] We address this issue of selection in our empirical analysis by controlling for the exhaustion of UI benefits before the application in the first-stage regression. The subsequent results are consistent with random assignment of applications to caseworkers.

2.3 Benefit prepayments

To mitigate the short-term income effect of longer application times, caseworkers may issue benefit prepayments. The aim of prepayments is to prevent applicants from facing liquidity constraints while awaiting the application decision. Applicants with pending applications, who are likely to be eligible for benefits, receive an payment equivalent to 90% of their expected benefit level in advance. This prepayment is issued starting from the fifth week of the application process and continues until the application is finalized.[14] The prepayments are deducted from the first benefit payments if benefits are awarded and remain outstanding claims when applications are rejected. Since the caseworker judges whether the applicant is expected to be ultimately eligible for benefits (based on incomplete information), the decision to grant prepayments also relies on the caseworker's judgment. Additionally, caseworkers may differ in their approach of granting prepayments.

2.4 Theoretical predictions

In our setting, applicants do not know ex ante the length of the welfare application process. Longer processing times therefore cannot affect the (initial) application decision, but are relevant during the application process pending the award decision of the caseworker. The overall effects of processing times on the take-up of benefits and employment are ambiguous: longer waiting times may discourage applicants to proceed with their applicants (*deterrence*), but longer periods of unemployment may also reduce applicants' subsequent employment or earnings potential (*deterioration*).

Deterrence implies that longer processing times reduce the take-up of welfare benefits and potentially increase employment. This effect may be largely mechanical: some individuals may withdraw their application while awaiting the award

[14] There are two other types of prepayments. First, applicants with liquidity constraints pending the application can request a loan to bridge the income gap, which can exceed the monthly benefits level and is paid within 8 weeks. Second, applicants with urgent liquidity constraints pending the application, such that they are unable to make ends meet, can request a modest loan of at most a few hundred euro specifically for groceries (not for e.g., utilities, rent or insurances), which are paid within two days. In the data, we cannot differentiate between the different types of prepayments. However, additional aggregate data from the municipality covering a largely comparable sample of welfare applicants shows that more than 95% of the prepayments are the prepayments amounting 90% of the expected benefit level from week 5 onwards.

decision, for example, after securing employment. As time proceeds, applicants may also become more inclined to secure income and avoid further application costs, particularly when they are liquidity constrained (see e.g., Basten et al., 2014; Card et al., 2007). With higher job search efforts and lower reservation wages, this may further reduce the take-up of welfare benefits and increase employment. When applicants with better labor market prospects withdraw their applications and resume working, the targeting of welfare benefits improves.

Deterioration occurs when long processing times directly reduce the subsequent employment or earnings outcomes of awarded applicants (Parsons, 1991). Long periods of inactivity due to postponed entry in the welfare program may reduce the employment or earnings potential.[15] During the application process, job search efforts of applicants are not monitored and reintegration services are not initiated yet. Applicants may also assume that work resumption implies the potential loss of accumulated welfare benefits up to that point, and lower their job search efforts. In recent analyses, more attention has also been paid to the potential role of financial stress: longer processing times lengthen the period during which applicants receive no income from benefits, worsening their financial situation. The resulting financial stress may, in turn, reduce their ability to search effectively for work (Dobbie & Song, 2015, 2020; Gathergood, 2012; Kaur et al., 2025). This mechanism may be particularly relevant in the context of means-tested welfare benefits, which are granted to applicants who have already limited or negative wealth at the time of application.

While longer processing times for welfare benefit applications prolong the temporary drop in income, the use of prepayments can largely offset this effect. One may therefore expect that prepayments have the potential to both decrease deterrence and deterioration effects. Since liquidity constraints are removed, prepayments may

[15] A negative relationship between unemployment duration and subsequent outcomes has been found among disability insurance applicants (Autor et al., 2015; Prenovitz, 2021) and among asylum seekers who face temporal employment restrictions upon arrival in a country (see e.g., Marbach et al., 2018; Fasani et al., 2021). This channel may seem less important in our study as the average application length is shorter (9 versus e.g. 61 weeks in Autor et al., 2015). Still, we argue that the absence of welfare to work services and monitoring of job search requirements pending the application decision may lead to higher levels of inactivity during the application as compared to when receiving welfare benefits. Additionally, prolonged unemployment may send a negative signal to employers regarding productivity (Kroft et al., 2013).

decrease the incentive to resume work. At the same time, prepayments may reduce financial stress and thus increase the likelihood of successful job search.

3 Data

3.1 Data sources

We use administrative individual-level data on all welfare applications submitted in the municipality of Rotterdam between 2013 and 2019. These data contain information on the application date, the main reason for application, and – if awarded benefits – the starting and ending date of the welfare benefit spell. Additionally, we have information on the caseworker assigned to the application (personal and caseworker team identifier).

We combine the application data with rich administrative records of Statistics Netherlands covering the period between 2012 and 2020. This yields individual-month panel data enabling us to follow applicants for at least one year and up to eight years both before and after the welfare application. The administrative records provide us with demographic characteristics (such as gender, age, and migration background), labor market outcomes and usage of several social security programs (welfare, UI, and disability insurance). The latter dataset also includes information on prepayments of welfare benefits during the application review period.

In total we observe the first welfare applications between 2013 and 2019 of 47,596 individuals. For our empirical analysis, we exclude applications by individuals younger than 27 or older than 49 at the time of application, as their applications are reviewed by different caseworkers (20,981)[16], applications for which the assigned caseworker is not observed (6,749), some outliers with applications longer than a full calendar year (367), and applications of which the caseworker reviews too little or too many applications in the according year (5,508).[17] This reduces our final sample

[16]In Figure A.1 in Appendix A, we see that the average age of the applicants assigned to a caseworker shows three spikes, namely at the ages 23, 38 and 49. This mirrors the fact that there are caseworkers mostly assessing applications for individuals below the age of 27, between the age of 27 and 49 and 50 years and older, respectively.

[17]Since we exploit information on the caseworker for causal inference, we impose a lower bound on the number of applications per caseworker to decrease measurement error. The upper bound

to 13,616 observations.[18]

3.2 Descriptive statistics

Figure 1 shows the distribution of application processing times and the corresponding probabilities of receiving benefit prepayments for our final sample.[19] About half of the applicants start receiving welfare benefits within the formal term of 8 weeks, 44 percent start receiving welfare benefits after 8 weeks, and only 6 percent of the applications do not result in welfare benefits receipt (either because of withdrawal, or because of a rejection). Furthermore, the propensity of receiving prepayments increases with the application processing time, especially after the first 4 weeks. In line with expectations, we see that applicants receive prepayments week 5 onward. Applicants who start receiving benefits sooner have less need of prepayments. About 12 percent of the applicants with the shortest application processing times (up to 4 weeks) receive prepayments, while this share increases to between 44 and 67 percent for applicants with longer processing times. Of the sample of applicants that do not enter welfare, 59 percent receive prepayments. For them, the prepayments cannot be deducted from the benefit payments and remain outstanding claims.

Table 1 shows the individual characteristics, labor market histories and cumulative labor market outcomes of our full sample (Column (1)) and different subsamples (Columns (2)-(6)). Starting with the full sample of applicants, about 48% is female and the majority is a first or second generation migrant (78%). 45% was employed

screens out administrative staff who assigned applications to themselves before assigning them to the caseworkers. We show the robustness of our results to different lower and upper bounds when discussing our main results in Section 5.

[18]In Table A.1 in Appendix A, we show that the selection rule based on age changes the sample. The sample of applicants aged 27-49 is statistically significantly different from our main sample, but differences are small. Remaining differences between the sample based on age and our main sample stem from the exclusion of applicants for which the caseworker is unobserved and not on the selection rule based on the number of applicants per caseworker or the outliers of applications longer than one year. The applicants with no observed caseworker have less distance to the labor market. If these caseworkers are unobserved as a result of quick withdrawal of the application, these applicants are likely not compliers. The selection rule based on the number of applicants per caseworker in a specific year is uncorrelated with individual characteristics.

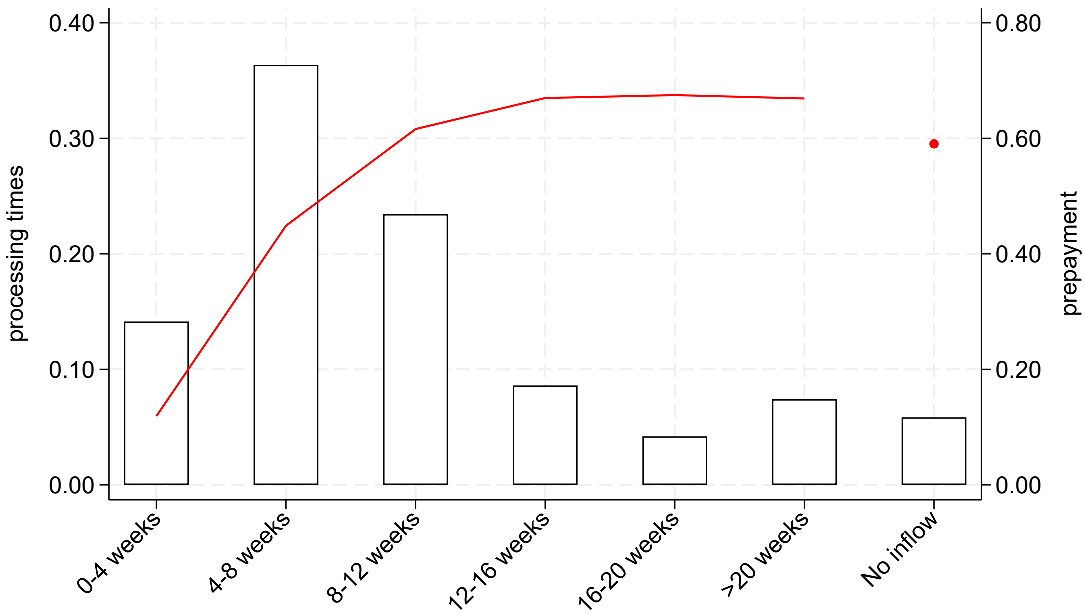
[19]The application processing times are calculated as the difference between the application date and the date of entry into welfare. However, in the case of rejected or withdrawn applications, we cannot calculate the application processing times, as the date of rejection or withdrawal is unobserved.

Table 1: Descriptive statistics of applicants by application outcome

								p-value difference		
	Full	Award	No award	Fast	Slow	Prepay	No prepay	Award vs. No award	Fast vs. Slow	Prepay vs. No prepay
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Demographics										
Age 27–31	0.32	0.32	0.37	0.33	0.31	0.33	0.31	0.00	0.00	0.00
Age 32–36	0.23	0.23	0.24	0.23	0.23	0.24	0.23	0.63	0.71	0.48
Age 37–41	0.17	0.17	0.15	0.17	0.18	0.17	0.17	0.05	0.10	0.63
Age 42–46	0.17	0.17	0.15	0.18	0.17	0.16	0.19	0.13	0.77	0.00
Age 47–49	0.10	0.10	0.09	0.10	0.10	0.10	0.10	0.13	0.04	0.62
Female	0.48	0.48	0.42	0.49	0.48	0.51	0.45	0.00	0.03	0.00
Native	0.22	0.22	0.29	0.23	0.20	0.23	0.21	0.00	0.01	0.00
First generation migrant	0.53	0.54	0.45	0.51	0.56	0.52	0.55	0.00	0.00	0.00
Second generation migrant	0.25	0.24	0.26	0.25	0.23	0.25	0.24	0.36	0.07	0.07
Labor market history and previous benefit eligibility										
Employed	0.45	0.44	0.63	0.46	0.42	0.42	0.46	0.00	0.17	0.02
Welfare benefit receipt	0.32	0.33	0.19	0.37	0.28	0.28	0.37	0.00	0.00	0.00
UI benefit receipt	0.22	0.22	0.25	0.28	0.15	0.18	0.26	0.00	0.00	0.00
Cumulative labor market outcomes in year after application										
Welfare (weeks)	40,65	42,10	17,32	41,91	42,31	43,26	40,99	0.00	0.84	0.00
Employment (weeks)	13,59	12,52	30,84	14,06	10,73	11,77	13,23	0.00	0.00	0.00
Welfare benefits (€)	7,528	7,837	2,554	7,641	8,063	8,029	7,653	0.00	0.00	0.00
Earnings (€)	4,058	3,501	13,037	4,282	2,597	3,208	3,780	0.00	0.00	0.00
Total income (€)	11,918	11,655	16,141	12,300	10,909	11,480	11,823	0.00	0.00	0.58
Observations	13,616	12,820	796	6,876	5,944	6,262	6,558			
Share of full sample	1.00	0.94	0.06	0.51	0.44	0.46	0.48			

Note: 'Award' is defined as that the application results in welfare receipt, 'No award' as that the application does not result in welfare receipt, 'Fast' is defined as entering welfare within 8 weeks, and 'Slow' as entering after 8 weeks. The p-values in columns (6-9) apply to t-tests of different means for the specific subsample. 'Welfare benefit receipt' and 'Employed' are dummies indicating the status in the year preceding or succeeding the application. 'UI benefit receipt' is based on the variable indicating the application reason in the application data of the city.

Figure 1: Distribution of application processing times (left) and percentage receiving prepayments (right)



and 22% was eligible for UI benefits in the preceding year, mirroring the fact that these applicants generally have a large distance to the labor market. On average, they receive benefits for more than three-quarters of the first year after applying, and spend one-quarter of the year in employment (note that individuals can be employed and receive additional benefits at the same time).

Next we compare different subsamples, starting with applicants awarded benefits (Column (2)) and applicants not awarded benefits (Column (3)). The p-values resulting from t-tests that assess the differences in means between these groups are shown in Column (8). Applicants who do not enter welfare as a result of their application are, on average younger, more often male, less likely to have a migration background, more frequently employed, and less likely to have received welfare benefits in the preceding year. This suggests that they have a smaller distance to the labor market. Not surprisingly, they work more and have higher earnings in the first year after application as well.

Similarly, we compare applicants who enter welfare within the formal application period of 8 weeks (Column (4)) with applicants who enter welfare after this period

(Column (5)). Applicants with fast applications are more often native or second generation migrants and received relatively often welfare or UI benefits in the year preceding the application.[20] This suggests that familiarity with and/or good understanding of the application system increases the probability of a fast application process and mirrors the fact that applicants who received UI benefits before applying are considered less complex to assess. Applicants who enter welfare faster are longer employed and have higher earnings, but the differences are not substantial.

Finally, Columns (6) and (7) compare applicants who receive prepayments pending their application and applicants who do not receive prepayments. Applicants with prepayments and applicants without prepayments differ the most on gender and migration background.[21] Women receive more prepayments, which might be explained by the relatively large share of recently-divorced or single applicants with young children in this group. The lower prepayment rate among first generation migrants may follow from limited familiarity with the system and/or language barriers that withhold them from requesting financial support. Again, the differences in post-application outcomes are small.

4 Methodology

4.1 Empirical approach

In our study, the applications for welfare benefits are processed by caseworkers, who determine the eligibility and the level of benefits. We exploit variation in the application processing times across caseworkers. This is possible since applications are quasi-randomly assigned to caseworkers; i.e., the assignment is random conditional on team, year, and exhaustion of UI benefits before the application. Furthermore,

[20]In the Netherlands, as in many other Western countries, migrants generally have worse socio-economic outcomes than natives. However, later generations tend to catch up and perform better than their parents, but don't close the gap completely (see e.g. Van Elk et al., 2024). Therefore, we take the migration generation into account.

[21]These differences are more pronounced when we condition on applications longer than 4 weeks (as prepayments are not paid within the first 4 weeks) and control for the application processing speed of the caseworker. This largely retaliates the mechanical relation between the application length and the probability of receiving prepayments. See Column (5) of Table C.4 in Appendix C.2 for these results.

it is important to stress that caseworkers only influence the outcomes of the welfare applicants via the processing times. Caseworkers involved with claim assessment are rarely in direct contact (by phone or in-person) with the applicant and are not involved in the monitoring of job search requirements and/or the reintegration activities (other caseworkers are specifically involved with monitoring and reintegration activities). Also, the benefit award decisions themselves provide no discretionary room for the caseworkers.[22]

Our empirical approach is inspired by an increasing number of studies exploiting judge or caseworker stringency as an instrumental variable. Kling (2006), Aizer & Doyle Jr (2015), Doyle Jr (2007, 2008), and Bhuller et al. (2020) use judge stringency to estimate the effects of judicial decisions on various socioeconomic and crime outcomes. Arni & Schiprowski (2019) and Van der Klaauw & Vethaak (2022) use caseworker stringency to estimate the effects of job search requirements on unemployed workers. Maestas et al. (2013) and French & Song (2014) use the assignment to disability examiners to demonstrate the negative effects of disability insurance benefits on employment rates.

To estimate the effect of the application processing time T_{ict} on the outcome Y_{ict} of individual i assigned to a caseworker in caseworker team c at time t, we use the following regression equation:

$$Y_{ict} = \alpha_{ct} + \delta T_{ict} + \mathbf{X}'_{it}\beta + \varepsilon_{ict} \tag{1}$$

The parameters α_{ct} are the interacted caseworker-team and year-fixed effects of team c of the caseworker assigned to the application filed in year t. Vector $\mathbf{X}_{it}$ includes individual characteristics, namely gender, age groups, migration background, a dummy indicating previous welfare receipt, a dummy indicating previous employment, and a dummy that indicates exhaustion of UI benefits before subsequently applying for welfare benefits. The parameter of interest δ describes the effect of the application processing time T_{ict}. We define T_{ict} as the time in weeks between the date of application and the date of entering welfare. Note that we observe T_{ict} only

[22] In subsection 5.1, we will show empirically that differences in award rates among caseworkers do not impact the award decision.

for applicants awarded benefits. In what follows, we will therefore first discuss the empirical approach to estimate the effects of application processing times among *awarded* applicants. Next, we will extend our analysis such that we can also include the applicants that do not enter welfare following the application.

Column (5) of Table 2 shows that application processing times T_{ict} are related to individual characteristics of the awarded applicants.We therefore rely on exogenous variation in application times that follows from the quasi-random assignment of applications to caseworkers who may differ in their processing speed. Stated differently, a welfare application that was approved after e.g. 4 weeks, might have been approved after e.g. 8 weeks if assigned to a different (or: slower) caseworker in the same caseworker team (or vice versa). We refer to this variation as the processing speed of the caseworker. We use the exogenous variation in processing times across caseworkers as instrument for the individuals' application processing time T_{ict}. This provides us with the following first-stage regression equation:

$$T_{ict} = \gamma_{ct} + \lambda Z_{j(i)t} + \mathbf{X}'_{it}\theta + \nu_{itc} \tag{2}$$

The instrumental variable $Z_{j(i)t}$ describes the speed of caseworker j assigned to the application of individual i. We calculate the caseworker speed measure as the conventional leave-out mean (similar to e.g., Maestas et al., 2013; Aizer & Doyle Jr, 2015; Bhuller et al., 2020). This implies that we consider all other (awarded) applications assigned to caseworker j (excluding the application of individual i) and calculate the mean processing time in this group. As a result, we can interpret the estimates of δ in the second stage Equation 1 as local average treatment effects (LATEs), i.e., the average treatment effect on the group of applicants for whom the application processing time depends on the processing speed of the caseworker to whom the applicant is assigned.

Inherent to our empirical strategy in which we exploit caseworker variation, we can only use the sample of applications for which we can identify a caseworker with an accurate caseworker speed measure. As previously discussed in Section 3, we therefore restrict the sample to applications assigned to caseworkers with at least 25 and at most 400 applications within the specific calendar year. The minimum of 25 is imposed to reduce measurement error in the calculated caseworker speed. The maximum of 400 is used to exclude a few teams which register applications to one staff member instead of individual caseworkers.[23] The remaining sample of 13,616 individual applications has been assigned to 162 different caseworkers. Each caseworker team has on average 23 caseworkers over the whole period. Caseworkers are in the data for two years on average.

To estimate the IV model described in Equations 1 and 2 we can only include observations with observed application processing times T_{ict}, i.e. awarded applications. We calculate exogenous values for $Z_{j(i)t}$ for all awarded and non-awarded applications from the average caseworker speed of all *awarded* applications assigned to caseworker j (again excluding the application of individual i).[24] At this point, the underlying assumption is that caseworker differences in application speed have equal effects on applicants who are awarded welfare benefits, and those who are not. We can use $Z_{j(i)t}$ to estimate reduced form regressions measuring the effect of caseworker speed on the probability of benefits take-up.

To mitigate the risk of liquidity constraints, longer applications are often combined with receipt of prepayments. As these prepayments may also affect application and employment behaviors, we are also interested in the effects of those prepayments. To investigate the effects of prepayments during the application period on welfare receipt and employment, we will estimate IV models comparable to those in Equations 1 and 2 with caseworker prepayment grant rates as instruments. This prepayment grant rate is again calculated as the leave-out mean among all other applicants assigned to caseworker j excluding applicant i. Since caseworkers typically grant prepayments 4 weeks after application (see subsection 2.3), we calculate the prepayment grant rate on applications longer than 4 weeks only.[25] As the propensity of receiving a prepayment is increasing in the application time, we will control for the caseworker speed in our empirical model to isolate the effect of prepayments.

[23] When testing the robustness of our first stage, we will also choose different thresholds.

[24] An alternative would be to calculate a counterfactual value of T_{ict} for the non-awarded applications. However, if the application processing times affect the probability of entering welfare, this value would probably be biased.

[25] The results are robust to using a prepayment grant rate based on applications of all lengths, but these results are less precisely estimated.

Table 2: Descriptive statistics, assignment of caseworker speed and the observed application processing time, sample of awarded applicants

	Explanatory variables		Dependent variables			
			Caseworker speed		**Processing time**	
	Mean	Standard Deviation	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
	(1)	(2)	(3)	(4)	(5)	(6)
Demographics						
Age 27–31	0.321	(0.467)	—		—	
Age 32–36	0.232	(0.422)	0.0307	(0.0420)	0.5052***	(0.1550)
Age 37–41	0.172	(0.378)	0.0183	(0.0547)	0.5180***	(0.1689)
Age 42–46	0.175	(0.380)	0.0262	(0.0550)	0.4154**	(0.1789)
Age 47–49	0.100	(0.300)	0.1950***	(0.0701)	0.6688***	(0.2369)
Female	0.483	(0.500)	-0.0077	(0.0401)	-0.5091***	(0.1143)
Native	0.219	(0.413)	—		—	
First generation migrant	0.536	(0.499)	0.0219	(0.0511)	0.6807***	(0.1539)
Second generation migrant	0.245	(0.430)	0.0328	(0.0548)	0.2356	(0.1789)
Labor market history and previous benefit eligibility						
Welfare benefit receipt	0.327	(0.469)	-0.0864	(0.0553)	-1.8231***	(0.1397)
Employed	0.439	(0.496)	0.0228	(0.0383)	-0.2217*	(0.1249)
F-statistic for joint significance			1.19		22.96	
[p-value]			[.304]		[.000]	
	Number of applications = 12,820			Number of caseworkers = 162		

Note: Column (3) shows OLS estimates of caseworker speed (=leave-out mean measured in weeks) on individual characteristics of welfare applicants. Column (5) shows a linear probability model of the observed processing time (in weeks) on individual characteristics of welfare applicants. All regressions include controls for exhaustion of UI benefits and interacted team and year fixed effects. Standard errors are robust and clustered at the caseworker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Justification of IV assumptions

Before we turn to the estimation results, we discuss the validity of caseworker speed as an instrumental variable for application processing times. Our primary focus is on the caseworker speed instrument for the sample of awarded applicants. The checks provide similar results for the full sample of applicants (including the 6% not awarded benefits). The discussion concerns the four assumptions of the instrumental variables approach: independence, exclusiveness, relevance and monotonicity.

Independence. For causal interpretation of λ in Equation 2, caseworker speed as an instrumental variable should be (quasi-)randomly assigned to individual applicants. Given that applications are randomly assigned to a caseworker *within* caseworker teams at the time of application, we control for fully interacted team- and year-fixed effects in the regression model. As explained in Section 2, the only exception to the quasi-randomized assignment is for applications that were filed after exhaustion of UI benefits.[26] Hence, we also control for UI exhaustion before applying for welfare benefits.[27] We test the conditional independence of the instrument by regressing the caseworker speed on individual characteristics of the applicants, while controlling for team and year fixed effects and exhaustion of UI benefits. The results for this test are shown in column (3) in Table 2. The joint F-test shows that individual characteristics do not predict the instrument (p-value equals 0.304).[28]

Exclusion restriction. In our context, the exclusion restriction states that the instrumental variable only affects the outcomes of the applicants through the application processing times. If caseworkers differ in any other dimension than their processing speed, it should be orthogonal to the caseworker speed instrument. Recall from Section 2 that the assigned caseworkers are not involved in the monitoring of job search requirements and/or in the provision of job search assistance for the welfare recipients (if awarded benefits) and have no discretionary room in the benefit award decision. Caseworkers, however, also decide on benefit prepayments in case of (expected) longer applications.[29] And faster caseworkers might differ in the prepayment grant rate. Still, in Appendix B.1 we provide detailed empirical evidence that the exclusion restriction holds. In sum, we find that: (i) The award decision is only affected by the processing speed of the caseworker and not by the stringency regarding the award decision. This result is consistent with the idea that

[26]See Figure B.1 in Appendix B. The vast majority of caseworkers review samples of applications with a 10-30% share of the applicants exhausted UI benefits before applying for welfare benefits. However, there is some bunching at zero and some outliers with a distinctly larger share of applicants who exhausted UI benefits.

[27]This is similar to Maestas et al. (2013) who use examiner stringency as instrumental variable for SSDI receipt. They expect that body system and terminal illness indicators were taken into account in the assignment of cases to examiners, and therefore control for these variables in their first-stage regression.

[28]A similar F-test shows that the instrumental variable caseworker speed for the full sample is also uncorrelated with individual characteristics (p-value equals 0.144).

[29]This resembles the situation of Bhuller et al. (2020), where judges not only decided on incarceration. Instead, trial decisions were multidimensional, as judges could also decide on fines, community service, probation and guilt.

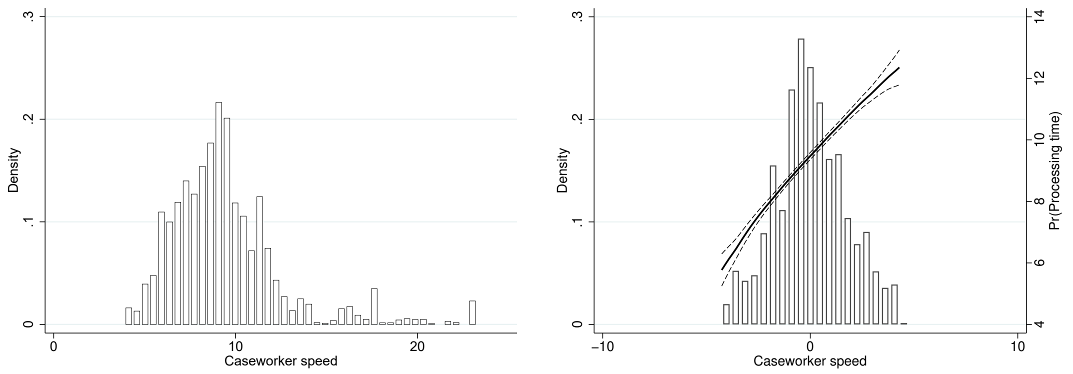
the award decision follows directly from the information provided by the applicant and that there is little or no discretion for caseworkers to deviate from this outcome. (ii) Caseworkers cannot use their discretion to impact the level of awarded benefits. (iii) Our results are robust to including the award rate and prepayment grant rate as additional regressors to our empirical model.

Instrument relevance. Figure 2 shows the distribution of the caseworker speed instrument (measured in weeks) both unconditional (panel a) and conditional (panel b) on UI exhaustion and interacted team and year fixed effects. The right-hand-side panel also adds a local linear regression that describes the relationship between the residual variation in caseworker speed and the residual variation in our treatment dummy T_{ict} (following Dahl et al. (2014) and Bhuller et al. (2020)). The unconditional distribution shows large variation in the processing speed of the caseworkers, with most of the mass between 5 and 15 weeks and a right tail. The conditional caseworker speed roughly follows a normal distribution. After conditioning on team-year fixed effects and UI exhaustion, the standard deviation of the distribution decreases from 3.12 to 2.05 weeks. The local linear regressions show that applicants assigned to a caseworker in the 5th percentile are awarded benefits after on average 6 weeks, compared to on average 12 weeks if assigned to a caseworker in the 95th percentile. This provides indicative evidence for a strong instrument.

Table B.2 in Appendix B shows the parameter estimates of λ of the first-stage Equation 2 for the sample of awarded applicants and for different subsamples of awarded applicants with different characteristics. The first-stage estimate for the full sample of awarded applicants is 0.749 (with a standard error of 0.025), which indicates that the application processing time largely depends on the average processing times of the caseworker (F-statistic = 917). Caseworker speed is therefore a relevant and strong instrument for the application processing times.[30] Additionally, Figure B.2 in Appendix B shows that the differences in caseworker speed are persistent over time (conditional on UI exhaustion and interacted team- and year-fixed

[30] Table B.3 in Appendix B shows the robustness of the first-stage to different thresholds for the minimum and maximum number of applications per caseworker and year, and to the inclusion of control variables. Consistent with the expectations, we see the largest change in the coefficients when we control for exhaustion of UI benefits before applying for welfare benefits.

Figure 2: Distribution of caseworker speed (left graph) and conditional on UI exhaustion and team and year fixed effects (right graph)



(a) Caseworker speed **(b)** Caseworker speed (demeaned)

Note: The histograms show the density of caseworker speed measured in weeks along the left y-axis (both figures). Residual variation in the treatment probability (application processing times) stems from a regression of the treatment on all variables listed in Table 1, UI exhaustion and fully interacted caseworker team and year fixed effects. The demeaned caseworker speed is conditional on UI exhaustion and team and year fixed effects. The probability of treatment is plotted on the right y-axis (right-hand-side figure) against leave-out mean caseworker speed along the x-axis. The solid line shows a local linear regression of residual variation in the treatment dummy on demeaned caseworker speed. The grey area reflects 90% confidence intervals.

effects). This suggests that some caseworkers are systematically faster than others.

Monotonicity. The monotonicity assumption states that applicants assigned to a caseworker with low speed (high average processing time) who started receiving welfare benefits after a certain period would also have received welfare benefits at least within that period if assigned to a caseworker with high speed (low average processing time), and vice versa. This assumption is violated if the processing time of different caseworkers differ across different groups of applicants (De Chaisemartin, 2017). Although this is not directly testable, Table B.2 in Appendix B shows that the first-stage estimates for all subsamples are strongly and positively significant and of comparable magnitude.[31] The positive first-stage coefficients for all different subsamples support the monotonicity assumption (Imbens & Angrist, 1994). Since the estimates do not differ much between individuals with different characteristics, we can also conclude that the group of compliers is largely comparable with the full

[31]The test for exclusion and monotonicity proposed by Frandsen et al. (2023) is not applicable in the current setting, as we use a continuous treatment variable and their approach requires a binary indicator.

Table 3: Reduced form estimates of caseworker processing speed on cumulative outcomes – full sample of applicants

Dependent variable:	Welfare receipt	Work	Welfare benefits	Earnings	Total income
	(1)	(2)	(3)	(4)	(5)
One year after application					
Caseworker speed (weeks)	-0.140**	-0.077	10	-31	-23
	(0.060)	(0.064)	(17)	(24)	(23)
Dependent mean	40.65	13.59	7,528	4,058	11,918
Number of workers			13,616		
Two years after application					
Caseworker speed (weeks)	0.014	-0.061	43	-44	-2
	(0.142)	(0.132)	(35)	(59)	(57)
Dependent mean	69.96	31.78	13,291	11,070	25,015
Number of workers			13,179		

Note: Time spent in welfare and work are measured in weeks. Total income includes benefits from welfare, UI and DI, earnings and income from self-employment. All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team-year fixed effects. Standard errors in parentheses are robust and clustered at the caseworker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

sample of awarded applicants.

5 Results

5.1 Overall effects of application processing times

We start our analysis by estimating reduced form regressions to measure the effects of caseworker speed on welfare and labor market outcomes of all welfare applicants. The results in Table 3 suggest that longer processing times have little effect on the cumulative outcomes of applicants one or two years after the application. We only observe a significant negative effect of longer applications on total time in welfare in the first year, which diminishes over the second year. This could be explained by withdrawals in the first years, whereas during the second year the effects of deterrence and deterioration may offset each other. All other coefficients are economically small and precisely estimated.

The absence of sizable effects may suggest that longer application processes have little or no impact on applicants' welfare and labor market outcomes, either through deterrence or deterioration. Alternatively, the effects of deterrence and deterioration may be of similar magnitude and offset each other. Moreover, the provision of prepayments may dampen the deterrence and deterioration effect. In the remainder of this section, we will therefore investigate the roles of deterrence, deterioration, and prepayments.

5.2 Deterrence: effects of application processing times on entering welfare

To analyze the deterrence mechanism, we estimate reduced form regressions with caseworker speed as the explanatory variable and a binary indicator of benefit take-up as the dependent variable. This approach allows us to assess whether the processing times that applicants face reduce the probability of entering welfare. Indeed, Table 4 shows a strong relationship between caseworker processing speed and the probability of entering welfare for the full sample of applicants. Having a caseworker who uses on average one week longer to review an application, reduces the probability of entering welfare with 0.62 percentage points. This effect is substantial, given that in total only 6% of the application are not awarded either due to withdrawal or rejection. Table 4 also shows that the award decision is only affected by the processing speed of the caseworker and not by the caseworker award rate. This confirms the fact that the award decision follows directly from the information provided by the applicant and that there is little or no discretion for caseworkers to deviate from this outcome. Higher award rates only follow from less withdrawn applications due to shorter waiting times. In Section 5.4, we will return to the results in Table 4 to examine the role of liquidity constraints in the deterrence channel. Specifically, we then assess whether individuals with a higher probability of receiving prepayments are more or less likely to withdraw from the application process.[32]

[32]The finding that longer applications reduce the probability of entering welfare is robust to excluding the caseworker award rate and/or the caseworker prepayment grant rate. Results are available upon request.

Table 4: Reduced form estimates of caseworker processing speed, caseworker award rate and caseworker prepayment grant rate on entering welfare by individual characteristics

		Caseworker speed		Caseworker award rate		Caseworker prepayment grant rate		
	Dep. mean	Coefficient	S.e.	Coefficient	S.e.	Coefficient	S.e.	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Full sample								
Full sample	0.942	-0.0062***	(0.0016)	0.0047	(0.0927)	-0.0099	(0.0253)	13,616
Gender								
Female	0.949	-0.0044**	(0.0019)	-0.0322	(0.1094)	-0.0088	(0.0321)	6,524
Male	0.935	-0.0079***	(0.0019)	0.0371	(0.1111)	-0.0095	(0.0337)	7,092
Age								
Age 27–35	0.935	-0.0063***	(0.0019)	-0.0394	(0.1194)	-0.0062	(0.0347)	7,043
Age 36–49	0.948	-0.0060***	(0.0019)	0.0521	(0.0925)	-0.0131	(0.0308)	6,573
Nationality								
Native	0.923	-0.0076***	(0.0027)	0.0925	(0.1648)	-0.0983*	(0.0546)	3,036
First generation migrant	0.950	-0.0055***	(0.0021)	0.0446	(0.0992)	0.0164	(0.0279)	7,237
Second generation migrant	0.939	-0.0063**	(0.0028)	-0.1661	(0.1254)	0.0145	(0.0441)	3,343
Welfare receipt in preceding year								
In welfare	0.965	-0.0015	(0.0020)	0.0669	(0.1041)	-0.0277	(0.0303)	4,344
Not in welfare	0.930	-0.0080***	(0.0018)	-0.0240	(0.1093)	-0.0026	(0.0317)	9,272
Employment in preceding year								
Employed	0.919	-0.0063***	(0.0022)	0.0449	(0.1523)	-0.0242	(0.0420)	6,123
Not employed	0.960	-0.0059***	(0.0017)	-0.0279	(0.0708)	0.0014	(0.0247)	7,493

Note: All caseworker stingencies are calculated as a leave-out mean. The caseworker processing speed is based on awarded applications only and the caseworker prepayment grant rate is based on applications longer than 4 weeks only. All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Standard errors in parentheses are robust and clustered at the caseworker level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Processing times that deter applicants from finishing their application may increase self-screening among workers with better labor market characteristics (Nichols & Zeckhauser, 1982; Kleven & Kopczuk, 2011), but also lower the take-up of benefits among those in greatest need (Deshpande & Li, 2019; Finkelstein & Notowidigdo, 2019). To analyze these potential effects, we re-estimate the reduced form regressions of caseworker speed and the probability of entering welfare for different subsamples. The results, reported in the different rows of Table 4, show that males, natives, and those not in welfare in the preceding year are more responsive to caseworker speed than females, (first generation) migrants and those who were in welfare in the preceding year, respectively.[33] Since the more responsive samples have what are generally considered better labor market prospects, the results suggest that longer processing times increase self-screening and therefore increase the targeting of the welfare program.

5.3 Deterioration: effects of application processing times on welfare and employment of awarded applicants

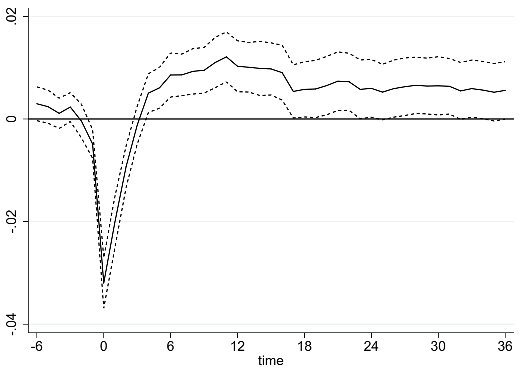
We next assess potential deterioration effects among awarded welfare applications. We do so by estimating the effects of longer processing times on the labor market and benefit outcomes of awarded applicants using the IV-approach as described in Section 4. Note that we can estimate this model only for the 94% subsample that are awarded benefits, which is also the subsample of interest.[34]

Figure 3 shows the monthly local average treatment effects of an increase of application processing times with one week on the four main outcomes, with $t = 0$ as the moment of application. We find substantial timing effects on the probability of welfare receipt. Specifically, applicants with longer applications have a lower probability of receiving benefits in the first months, but this effect reverses after three months (graph (a)). The (positive) effect is smaller, but it lasts for a longer

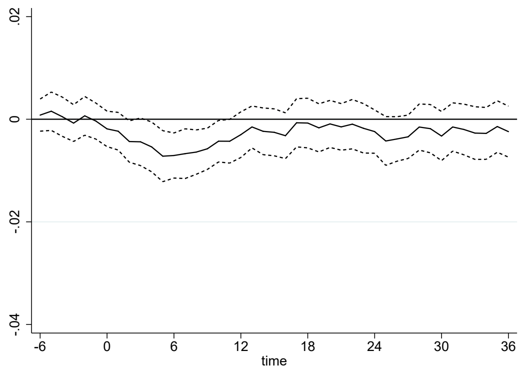
[33] Note that for all subsamples – if anything – the caseworker speed predicts the award decision and not the award rate.

[34] By focusing on the subsample of awarded applicants, we estimate the direct effect of the application process on subsequent labor market and benefit outcomes, while excluding the indirect effect of the application process on these outcomes through the award decision (Autor et al., 2015).

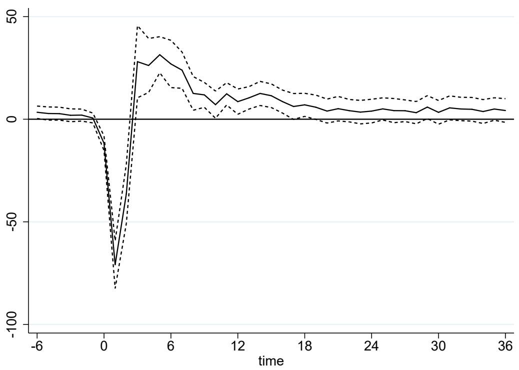
Figure 3: Effects of application processing times on welfare and employment outcomes among award applicants– instrumental variable estimates



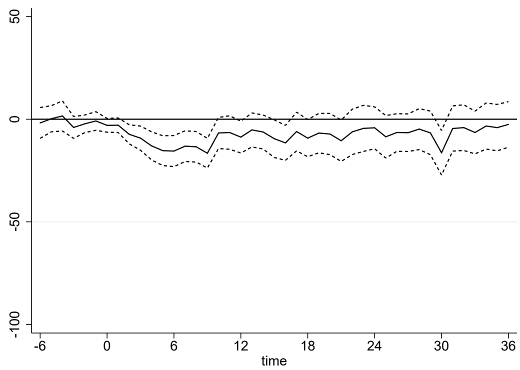
(a) Welfare receipt



(b) Employment



(c) Welfare benefits



(d) Earnings

Note: Vertical axis displays the probability (top panels) and amounts in Euros (bottom panels). Regressions per month include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Dashed lines display 95% confidence interval based on standard errors clustered at the caseworker level. $t = 0$ is the welfare benefit application date.

period and is still (marginally) significant after three years. A similar pattern is observed for welfare benefits, with a negative spike immediately after the application and a positive spike a few months later (graph (c)). The effects on welfare receipt and benefits reflect a predominantly mechanical effect that follows from comparing applicants with shorter and longer application times (originating from differences in caseworker speed), where the former group enters welfare more quickly (and probably also leaves welfare more quickly), while the latter group catches up in the later months. Perhaps more strikingly, the two right-hand-side graphs of Figure 3 show that longer processing times have a small but significant negative effect on the

Table 5: Effects of application processing time on cumulative outcomes among awarded applicants – instrumental variable estimates

Dependent variable:	Welfare receipt	Work	Welfare benefits	Earnings	Total income
	(1)	(2)	(3)	(4)	(5)
One year after application					
Processing time (weeks)	0.033	-0.260***	61***	-123***	-63**
	(0.081)	(0.087)	(23)	(30)	(28)
Dependent mean	42.10	12.52	7,837	3,501	11,655
Number of workers			12,820		
Two years after application					
Processing time (weeks)	0.438**	-0.363**	145***	-222***	-79
	(0.194)	(0.175)	(47)	(73)	(70)
Dependent mean	72.55	29.90	13,825	9,984	24,424
Number of workers			12,418		

Note: Time in welfare and work are measured in weeks. Total income includes benefits from welfare, UI and DI, earnings and income from self-employment. All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team-year fixed effects. Standard errors in parentheses are robust and clustered at the caseworker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

employment probability and earnings of the applicants in the first year after the application (graphs (b) and (d)).

Table 5 shows the estimated effects of the application processing times on cumulative outcomes one and two years after the application. We find that longer processing times increase dependency on welfare and reduce employment. Hence, the increased welfare dependency in the longer term are larger than the immediate (negative) effects in the short term. Moreover, the effects on welfare and labor market outcomes are larger after two years than after the first year. For one additional week of waiting, awarded applicants will on average receive welfare benefits for 0.44 weeks extra and work 0.36 weeks less in the two subsequent years. Concurrently, applicants receive more welfare benefits and have lower earnings. The effect of longer processing times on total income is negative but not significant after two years. These results show that the deterioration mechanism does play an important role in the welfare and labor market outcomes of (awarded) applicants.

Table C.3 in Appendix C shows cumulative estimates after one year for different subgroups of applicants.[35] Similar to the deterrence effect in the previous subsection, we find that applicants with better labor market prospects are more affected by longer processing times. For them, longer processing times reduce employment and earnings the most. The difference is particularly large between natives and second-generation migrants, and first-generation migrants, where the welfare and labor market outcomes of the latter group seem to be almost non-responsive to longer processing times.

A key assumption underlying the above findings is that differences in application waiting times between caseworkers are not correlated with differences in the use of prepayment grants across caseworkers. To back up our findings, we therefore include the award propensity and the propensity to grant prepayments of the caseworker as additional regressors to the model. Table C.1 in Appendix C, which shows the results of this robustness tests, yields estimated effects that are almost unaffected. Additionally, Table C.2 in Appendix C shows that our results are robust to the use of quarter-fixed effects instead of year-fixed effects.

5.4 Effects of benefit prepayments

We finally turn to the effects of prepayments to investigate the role of liquidity constraints in the deterrence and deterioration channels. Since liquidity constraints may increase the incentive to find work but also may induce financial stress that withhold applicants from successful job search, the effect of prepayments is theoretically ambiguous.

Similar to the application processing time, the receipt of benefit prepayments depends on individual characteristics and the caseworker who is assigned to review the application.[36] We make use of the 'caseworker prepayment grant rate', which, as mentioned before, represents differences in how often caseworkers grant prepayments. These differences are inferred from the subsample of applicants with applications longer than 4 weeks. Table 6 shows how caseworkers affect the receipt

[35] The results after two years provide the same conclusions.

[36] For instance, Table C.4 in Appendix C shows that women and natives are more likely to receive prepayments than other groups.

Table 6: Effect of caseworker processing speed and prepayment grant rate on the probability of prepayment receipt among awarded applicants

	(1)	(2)	(3)
Caseworker processing speed	0.0297***	—	0.0210***
	(0.0031)		(0.0047)
Caseworker prepayment grant rate	—	0.5286***	0.3275***
		(0.0488)	(0.0845)
Number of applications = 12,820		Number of caseworkers = 162	

Note: All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Standard errors in parentheses are robust and clustered at the caseworker level. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

of prepayments. Columns (1) and (2) show that both the caseworker application processing speed and the prepayment grant rate predict the receipt of prepayments. Finally, column (3) shows that – in a combined model – both the caseworker application processing speed and the prepayment grant rate predict the receipt of prepayments. Applicants who have to wait longer on their benefits thus receive prepayments more often, but also applicants who are assigned a caseworker who is more lenient in granting prepayments receive prepayments more often.[37]

The differences in caseworker prepayment grant rates provide us with an exogenous source of variation in the receipt of prepayments. Similar to our earlier analyses, we exploit this variation to estimate the causal effects on individual outcomes. Knowing that the probability of prepayment receipt is explained by both the caseworker prepayment grant rate and the caseworker speed, we control for the caseworker speed in our empirical model.[38]

Starting with the deterrence channel, we investigate whether individuals with a higher probability of receiving prepayments are more or less likely to withdraw from the application process. For this, we return to Table 4, where we estimate the

[37]From Table C.5 in Appendix C we also conclude that the probability of receiving prepayments for applicants with applications longer than 4 weeks depends on the caseworker speed and the caseworker prepayment grant rate. This means that the receipt of prepayments is time dependent, also after the threshold of 4 weeks.

[38]Table C.4 in Appendix C shows that the caseworker prepayment grant rate is uncorrelated with individual characteristics when controlling for caseworker speed (F-stat=1.29, p-value=.243). We account for the caseworker processing speed to control for the potential simultaneous effect of the processing times on the probability of receiving prepayments.

Table 7: Effects of both application processing times and prepayments on cumulative outcomes among awarded applicants - instrumental variable estimates

Dependent variable:	Welfare	Work	Welfare benefits	Earnings	Total income
	(1)	(2)	(3)	(4)	(5)
One year after application					
Processing time (weeks)	0.139	-0.723**	86**	-316***	-242**
	(0.272)	(0.282)	(66)	(107)	(99)
Prepayment	-2.666	11.664*	-606	4,881**	4,492**
	(5.494)	(6.512)	(1,524)	(2,414)	(2,274)
Dependent mean	42.10	12.52	7,837	3,501	11,655
Number of workers			12,820		
Two years after application					
Processing time (weeks)	0.818	-1.305**	185	-640***	-457**
	(0.575)	(0.535)	(138)	(242)	(229)
Prepayment	-9.522	23.586*	-1,002	10,479*	9,452*
	(13.010)	(13.019)	(3,224)	(5,519)	(5,151)
Dependent mean	72.55	29.90	13,825	9,984	24,424
Number of workers			12,418		

Note: Results of IV models with two endogenous variables (application processing times and prepayments) and two instrumental variables (caseworker speed and caseworker prepayment grant rate). Time in welfare and work are measured in weeks. All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Standard errors in parentheses are robust and clustered at the caseworker level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

probability of entering welfare based on caseworker speed, caseworker award rate, and caseworker prepayment grant rate. The findings suggest that prepayments have little impact on the probability of entering welfare, with only a marginally significant effect observed among native applicants.

We next turn to the effect of prepayments on welfare receipt and labor market outcomes of awarded applicants (see Table 7). This allows us to investigate changes in the deterioration effect. Specifically, we estimate an instrumental variables model with both the effects of longer processing times and of the provision of prepayments; these are instrumented with the caseworker speed and the caseworker prepayment grant rate. The effects of processing times are more substantial when estimated simultaneously with the effects of prepayments (compared to the results in Table 5). An extension of the application process with one week reduces the time employed in the first two years after application with on average 1.3 weeks, and lowers earnings with more than 600 Euro. In contrast, prepayments increase employment substantially and double earnings with roughly 10,000 Euro.[39,40] In addition, Table C.8 in Appendix C shows the cumulative effects of prepayments after one year for different subgroups of applicants. We again observe the largest effects for the groups with better labor market characteristics, especially among natives. The above findings are consistent with the idea that prepayments alleviate financial stress, which in turn increases the likelihood of successful job search.

Taken together, our analysis shows robust evidence for the deterioration effects of application processing times in the Dutch welfare system, which are in part reduced by the provision of prepayments. Prepayments probably reduce financial stress, which would otherwise withhold applicants from successful job search.

6 Conclusion

This paper investigates the causal impact of welfare application processing times on welfare receipt and employment. Unemployed workers submit their welfare applications to the city offices, providing detailed information regarding their living situation, income, wealth, and other relevant factors. Caseworkers evaluate these applications to determine eligibility and benefit levels, sometimes requiring additional information, which extends the processing period and delays the award decision. Longer application processing times can affect applicants in two ways. First, as the application process continues to lengthen, applicants may withdraw their application, for example as they find work (i.e. the *deterrence* mechanism). Second, longer processing times may reduce the applicants' subsequent labor market outcomes (i.e. the *deterioration* mechanism). To estimate the causal effects of processing times through these mechanisms, we exploit variation in application pro-

[39]For ease of interpretation, consider that the reduced form estimate of the prepayment grant rate on earnings equals roughly 2,200 euro. This mirrors the fact that the standard deviation of the demeaned prepayment grant rate is limited to 0.108.

[40]In Appendix C, we show the robustness of our estimated effects of processing times. Table C.6 shows that the results are very similar for the subsample with applications longer than 4 weeks. Table C.7 shows similar effects of processing times when estimated in a separate model.

cessing speed among caseworkers and the quasi-random assignment of applications to caseworkers.

Our main research findings can be summarized as follows. First, longer application processing times have no sizable effects on the average outcomes of applicants. This appears to result from the opposing effects of deterrence and deterioration, which effectively cancel each other out. Second, we find strong evidence of deterrence effects. Having a caseworker who needs one additional week to review an application leads to a 0.62 percentage point decrease in benefit take-up. Deterrence is strongest among applicants with better labor market characteristics, such as men, natives and applicants who did not receive welfare benefits in the preceding year. Third, we also find empirical support for the deterioration mechanism among awarded applicants. Longer processing times increase welfare dependency and reduce labor market attachment among (awarded) applicants. These results are also strongest among those with initially better labor market prospects. Finally, we show that prepayments promote the employment and earnings of (awarded) applicants, suggesting that alleviating financial stress fosters more effective job search.

Our findings suggest that extended processing times may serve as a screening device that deters applicants with stronger labor market prospects from completing the application process. It is therefore likely that the deterred applicants are, on average, able to compensate the loss of benefit income on the labor market. However, this type of improved targeting comes at a cost: awarded applicants who face longer processing times show worse labor market outcomes than those with shorter processing times. This aligns with the findings of Autor et al. (2015), who document long-lasting reductions in employment and earnings due to long processing times for SSDI applicants. Our findings show that much shorter processing times of welfare benefit applications also have the potential to significantly reduce post-application employment and earnings.

Our analysis provides a novel perspective on the trade-off in social benefit programs between providing timely income security and ensuring the accuracy of benefit award decisions. Immediate benefits, combined with ex post eligibility checks, initially offer income security, but risk diluting the deterrence effect of application processing times and causing financial stress for rejected applicants with debts from benefit overpayments. Our results also highlight the adverse consequences of prolonged application processing times for (eligible) applicants experiencing liquidity constraints. These results are consistent with previous studies pointing at the potentially detrimental effects of severe liquidity constraints on individuals (Dobbie & Song, 2015; Gathergood, 2012).

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A Data: additional tables and figures

Figure A.1: Distribution of mean age of the applicants by caseworker

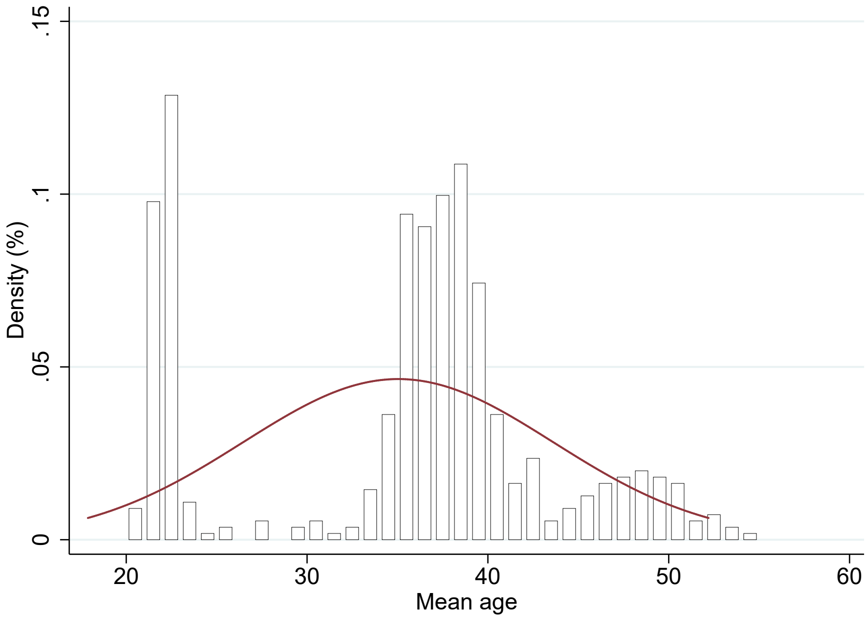


Table A.1: Sample selections and descriptives of the samples

						p-value difference			
	All first applicants	Applicants aged 27-49	+ Non-missing caseworker	+ Caseworkers with 25-400 applicants	+ Applications $\leq$ 1 year (main sample)	Main sample vs. All first applicants	Main sample vs. Aged 27-49	Main sample vs. Aged 27-49 + Non-missing	Main sample vs. Aged 27-49 + Non-missing + 25-400 applicants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Demographics									
Age 27–31	0.175	0.314	0.324	0.324	0.324	0.00	0.00	1.00	0.83
Age 32–36	0.130	0.232	0.233	0.234	0.233	0.00	0.78	0.92	0.51
Age 37–41	0.098	0.176	0.171	0.171	0.171	0.00	0.04	0.86	0.96
Age 42–46	0.099	0.178	0.173	0.173	0.173	0.00	0.07	0.91	0.62
Age 47–49	0.057	0.101	0.099	0.099	0.099	0.00	0.16	0.83	0.91
Female	0.464	0.463	0.481	0.483	0.479	0.00	0.00	0.44	0.13
Native	0.229	0.213	0.221	0.222	0.223	0.05	0.00	0.40	0.64
First generation migrant	0.513	0.567	0.532	0.531	0.532	0.00	0.00	0.72	0.87
Second generation migrant	0.258	0.220	0.246	0.247	0.246	0.00	0.00	0.69	0.53
Labor market history and previous benefit eligibility									
Welfare benefit receipt	0.281	0.317	0.310	0.310	0.319	0.00	0.37	0.00	0.00
Employed	0.394	0.398	0.448	0.449	0.451	0.00	0.00	0.22	0.36
Exhaustion of UI benefits	0.140	0.184	0.219	0.220	0.221	0.00	0.00	0.24	0.61
Observations	47,596	26,615	19,491	19,124	13,616				

Note: The p-values in columns (6-9) apply to t-tests of different means for the specific subs-sample and full sample. The main sample refers to the sample used in the main analysis in this paper. ‘Welfare benefit receipt’ and ‘Employed’ are dummies indicating the status in the year preceding the application. ‘Exhaustion of UI benefits’ is based on the variable indicating the application reason in the application data of the city.

B Justification of the assumptions

B.1 Exclusion restriction

Here we describe empirical evidence in support of the exclusion restriction. First, in (Section 5.2) of our analysis – when we estimate reduced form regressions using caseworker speed and caseworker award rate to predict the probability of benefit receipt – we will show that the award decision is only affected by the processing speed of the caseworker and not by the stringency regarding the award decision. This result is consistent with the idea that the award decision follows directly from the information provided by the applicant and that there is little or no discretion for caseworkers to deviate from this outcome. Changes in the award rate then only follow from behavioral responses by the applicants and not from caseworker decisions.

As a second test on the validity of the exclusion restriction, we empirically test the possibility that caseworkers use their discretion to impact the level of awarded benefits. Table B.1 shows the relationship between the caseworker processing speed and the benefit payments if awarded benefits. Since overdue payments stemming from the application period are paid retroactively and potential prepayments are deducted from the first payment, we are interested in the welfare benefit levels after the first payment.[41] Columns (2)-(4) show that these subsequent payments are unaffected by caseworker speed.[42] Only the fourth payment is significantly affected at the 10-percent level, but this effect is economically small and could as well be the result of changes in the composition of the sample that remains in welfare due to the treatment. (As expected, Column (1) shows that the first welfare payments are on average higher and that caseworker speed is strongly correlated with the level of the first welfare payment, indicating that those who have to wait longer receive a

[41]Note that the first welfare payment does not necessary coincide with the first month after application.

[42]Conditional on household status, there is little variation in the level of welfare benefits. Some (downward) changes in the benefit level might originate from household income, inhabiting children or outstanding claims. Most of the variation in the income of welfare recipients stems from the different fiscal income supplements that we do not observe, such as housing subsidies, child subsidies, and health insurance subsidies. The caseworkers assessing the applications do not decide on these supplements.

Table B.1: Effect of caseworker processing speed on the monthly level of welfare benefit payments

Dependent variable:	First payment (1)	Second payment (2)	Third payment (3)	Fourth payment (4)
Caseworker speed (weeks)	122.0***	0.3	2.1	2.6**
	(7.0)	(1.7)	(1.6)	(1.3)
Dependent mean (s.d.)	1,911 (1,358)	857 (374)	868 (387)	859 (322)
Number of applicants	12,340	11,231	10,937	10,369

Note: All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Standard errors in parentheses are robust and clustered at the caseworker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

higher first payment.)

Third, if caseworkers differ in the likelihood that they grant prepayments and this is correlated with their application processing speed, this is a potential threat to the exclusion restriction. Therefore, we will check the robustness of our main results by including the award rate and prepayment rate as additional regressors to our empirical model in Section 5.

B.2 Additional tables and figures

Figure B.1: Distribution of mean of the applicants who applied after exhaustion of UI benefits by caseworker

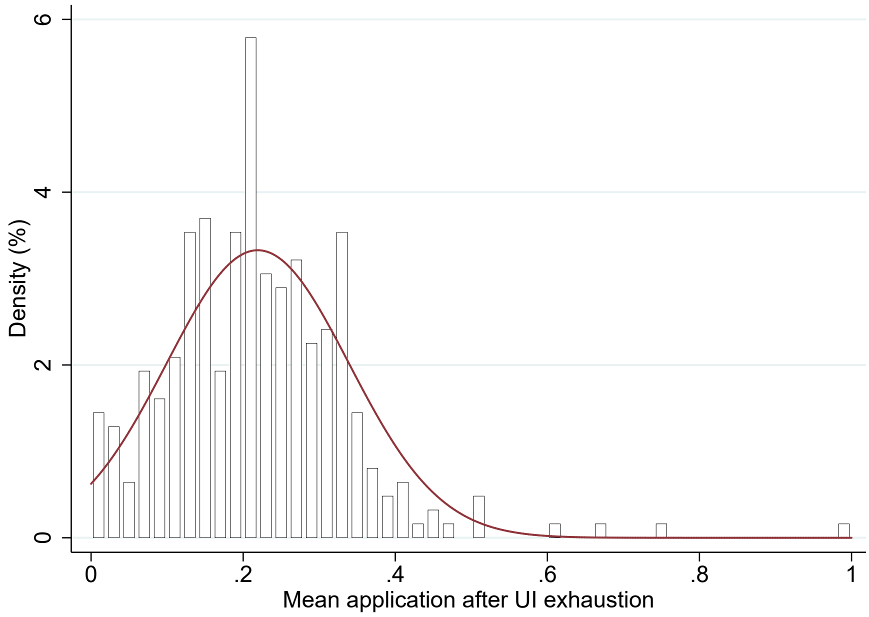
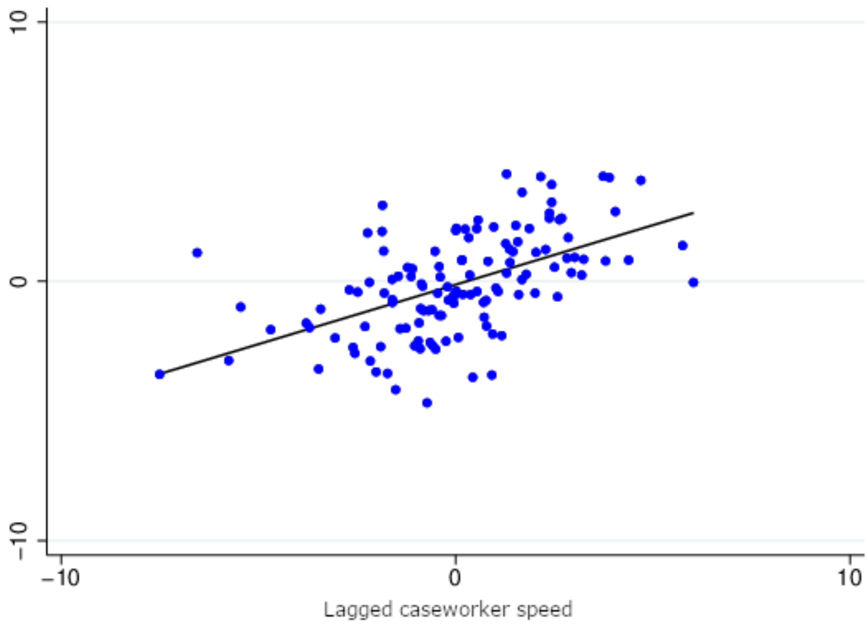


Table B.2: First-stage estimates of caseworker speed on processing times by subgroups – sample of awarded applicants

	Coefficient	S.e.	F-stat	N	Dependent Mean
	(1)	(2)	(3)	(4)	(5)
Full sample					
Full sample	0.749***	(0.025)	917	12,820	9.41
Gender					
Female	0.733***	(0.041)	323	6,189	9.25
Male	0.768***	(0.042)	342	6,631	9.56
Age					
Age 27–35	0.698***	(0.037)	358	6,588	9.27
Age 36–49	0.810***	(0.041)	395	6,232	9.56
Nationality					
Native	0.828***	(0.070)	137	2,803	8.92
First generation migrant	0.737***	(0.034)	482	6,877	9.80
Second generation migrant	0.682***	(0.049)	192	3,140	8.99
Welfare receipt in preceding year					
In welfare in preceding year	0.651***	(0.045)	206	4,194	8.29
Not in welfare in preceding year	0.778***	(0.028)	760	8,626	9.96
Employment history					
Work in preceding year	0.729***	(0.036)	419	5,625	9.11
No work in preceding year	0.763***	(0.035)	466	7,195	9.65

Note: All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Standard errors in parentheses are robust and clustered at the caseworker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure B.2: Caseworker speed in period t and $t-1$



Note: The black line shows the calculated prediction of the linear relationship between the caseworker speed and its lagged value.

Table B.3: First-stage estimates using different sample selections on caseworkers and different controls

Sample selection	20-400	25-400†	30-400	25-300	25-500
	(1)	(2)	(3)	(4)	(5)
Panel A. No additional controls					
Caseworker speed	0.751***	0.773***	0.777***	0.773***	0.772***
	(0.026)	(0.026)	(0.028)	(0.026)	(0.026)
F-stat. (Instrument)	860	916	746	916	908
Panel B. Add exhaustion of UI benefits					
Caseworker speed	0.736***	0.758***	0.761***	0.758***	0.757***
	(0.026)	(0.026)	(0.030)	(0.026)	(0.026)
F-stat. (Instrument)	789	821	665	821	818
Panel C. Add demographic controls					
Caseworker speed	0.735***	0.756***	0.759***	0.756***	0.755***
	(0.026)	(0.026)	(0.029)	(0.026)	(0.026)
F-stat. (Instrument)	792	832	684	832	829
Panel D. Add labor market history controls					
Caseworker speed	0.730***	0.749***	0.750***	0.749***	0.748***
	(0.025)	(0.025)	(0.028)	(0.025)	(0.025)
F-stat. (Instrument)	853	889	715	889	885

Note: †The baseline analysis uses caseworkers meeting 25-400 benefits recipients. All regressions include local office fixed effects interacted with month fixed effect. The demographic controls are age groups, gender and migration background dummies. The labor market history controls are previous welfare receipt and employment dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Results: additional tables

C.1 Effects of application processing times on labor market and benefit outcomes: additional tables

Table C.1: Effects of application processing time on cumulative outcomes among awarded applicants – instrumental variable estimates with additional caseworker stringency controls

Dependent variable:	Welfare receipt	Work	Welfare benefits	Earnings	Total income
	(1)	(2)	(3)	(4)	(5)
One year after application					
Processing time (weeks)	0.033	-0.319**	63	-151***	-94**
	(0.124)	(0.132)	(42)	(50)	(45)
Dependent mean	42.10	12.52	7,837	3,501	11,655
Number of workers			12,820		
Two years after application					
Processing time (weeks)	0.543*	-0.515*	159*	-282**	-126
	(0.298)	(0.285)	(82)	(134)	(111)
Dependent mean	72.55	29.90	13,825	9,984	24,424
Number of workers			12,418		

Note: All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Additional caseworker stringency controls are the award rate and the prepayment rate, which are computed as leave-out means. Time in welfare and employment are measured in months. Total income includes benefits from welfare, UI and DI, earnings and income from self-employment. Standard errors in parentheses are robust and clustered at the caseworker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Effects of application processing time on cumulative outcomes among awarded applicants – instrumental variable estimates with quarter fixed effects

Dependent variable:	Welfare receipt	Work	Welfare benefits	Earnings	Total income
	(1)	(2)	(3)	(4)	(5)
One year after application					
Processing time (weeks)	0.168	-0.312***	74	-147***	-74**
	(0.105)	(0.117)	(30)	(40)	(37)
Dependent mean	42.10	12.52	7,837	3,501	11,655
Number of workers			12,820		
Two years after application					
Processing time (weeks)	0.684***	-0.397*	166***	-254**	-95
	(0.260)	(0.240)	(63)	(99)	(92)
Dependent mean	72.55	29.90	13,825	9,984	24,424
Number of workers			12,418		

Note: All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with quarter year fixed effects. Time in welfare and work are measured in weeks. Total income includes benefits from welfare, UI and DI, earnings and income from self-employment. Standard errors in parentheses are robust and clustered at the caseworker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Effects of application processing time on cumulative outcomes after one year for different demographic groups of awarded applicants– instrumental variable estimates

Dependent variable:	Welfare receipt	Work	Welfare benefits	Earnings	Total income
	(1)	(2)	(3)	(4)	(5)
A. GENDER:					
1. Female					
Estimate	-0.021	-0.244*	47	-132***	-87**
(s.e.)	(0.119)	(0.135)	(32)	(43)	(35)
Dependent mean	42.38	12.98	7,837	3,252	11,391
Number of workers			6,189		
2. Male					
Estimate	0.079	-0.294***	80**	-119***	-40
(s.e.)	(0.116)	(0.106)	(31)	(43)	(40)
Dependent mean	41.84	12.09	7,836	3,733	11,903
Number of workers			6,631		
B. AGE:					
1. Aged 27-35					
Estimate	0.132	-0.331**	90***	-189***	-109***
(s.e.)	(0.125)	(0.135)	(34)	(50)	(40)
Dependent mean	41.11	13.75	7,535	3,965	11,777
Number of workers			6,588		
2. Aged 36-49					
Estimate	-0.060	-0.212*	39	-64	-18
(s.e.)	(0.101)	(0.111)	(28)	(40)	(41)
Dependent mean	43.14	11.22	8,156	3,009	11,527
Number of workers			6,232		
C. NATIONALITY:					
1. Native					
Estimate	0.113	-0.396***	62*	-222***	-169***
(s.e.)	(0.145)	(0.154)	(35)	(65)	(65)
Dependent mean	41.27	14.55	7,443	4,360	12,175
Number of workers			2,803		
2. First generation migrant					
Estimate	0.009	-0.107	48	-59	-14
(s.e.)	(0.120)	(0.123)	(34)	(123)	(32)
Dependent mean	42.52	11.58	8,111	2,977	11,395
Number of workers			6,877		
3. Second generation migrant					
Estimate	0.031	-0.496***	99**	-161**	-58
(s.e.)	(0.182)	(0.185)	(44)	(73)	(57)
Dependent mean	41.90	12.75	7,587	3,879	11,762
Number of workers			3,140		
D. WORK:					
1. Employed in preceding year					
Estimate	0.165	-0.275*	100***	-176***	-84**
(s.e.)	(0.124)	(0.155)	(34)	(48)	(38)
Dependent mean	39.76	21.04	6,951	5,689	13,079
Number of workers			5,625		
2. Not employed in preceding year					
Estimate	-0.060	-0.259***	28	-87***	-57
(s.e.)	(0.095)	(0.085)	(27)	(33)	(37)
Dependent mean	43.92	5.86	8,529	1,789	10,543
Number of workers			7,195		

Note: All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Time in welfare and work are measured in weeks. Total income includes benefits from welfare, UI and DI, earnings and income from self-employment. Standard errors in parentheses are robust and clustered at the caseworker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.2 Effects of benefit prepayments: additional tables

Table C.4: Descriptive statistics, assignment of caseworker prepayment grant rate and the observed prepayments

	Explanatory variables		Dependent variables			
			Caseworker prepayment grant rate		**Prepayment**	
	Mean	Standard Deviation	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
	(1)	(2)	(3)	(4)	(5)	(6)
Demographics						
Age 27–31	0.321	(0.467)	—		—	
Age 32–36	0.232	(0.422)	-0.0021	(0.0022)	-0.0090	(0.0115)
Age 37–41	0.172	(0.378)	-0.0048**	(0.0023)	-0.0169	(0.0130)
Age 42–46	0.175	(0.378)	-0.0034	(0.0024)	-0.0509***	(0.0129)
Age 47–49	0.100	(0.300)	0.0016	(0.0029)	-0.0315*	(0.0168)
Female	0.483	(0.500)	-0.0023	(0.0017)	0.0399***	(0.0094)
Native	0.219	(0.413)	—		—	
First generation migrant	0.536	(0.499)	0.0017	(0.0023)	-0.0382***	(0.0116)
Second generation migrant	0.245	(0.430)	0.0020	(0.0023)	-0.0201	(0.0134)
Labor market history and previous benefit eligibility						
Welfare benefit receipt	0.327	(0.469)	-0.0016	(0.0020)	-0.0919***	(0.0095)
Employed	0.439	(0.496)	0.0002	(0.0018)	-0.0289***	(0.0081)
F-statistic for joint significance			1.29		17.49	
[p-value]			[.243]		[.000]	
	Number of applications = 12,820			Number of caseworkers = 162		

Note: Column (3) shows OLS estimates of caseworker prepayment grant rate (=leave-out mean) on individual characteristics of welfare applicants. Column (5) shows a linear probability model of the observed processing time (in weeks) on individual characteristics of welfare applicants. All regressions include controls for caseworker speed, exhaustion of UI benefits and interacted team and year fixed effects. Standard errors are robust and clustered at the caseworker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Effect of caseworker processing speed and prepayment grant rate on the probability of prepayment receipt – sample of applications longer than 4 weeks

	(1)	(2)	(3)
Caseworker processing speed	0.0223***	—	0.0150***
	(0.0030)		(0.0045)
Caseworker prepayment grant rate	—	0.4300***	0.2773***
		(0.0498)	(0.0928)
Number of applications = 10,894		Number of caseworkers = 162	

Note: All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Standard errors in parentheses are robust and clustered at the caseworker level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table C.6: Effects of both application processing times and prepayments on cumulative outcomes among applicants with applications longer than 4 weeks - instrumental variable estimates

Dependent variable:	Welfare	Work	Welfare benefits	Earnings	Total income
	(1)	(2)	(3)	(4)	(5)
One year after application					
Processing times	0.132	-0.669**	98	-323***	-237**
	(0.258)	(0.270)	(61)	(111)	(101)
Prepayment	-2.786	12.856*	-231	6,345**	6,468**
	(6.097)	(7.193)	(1,575)	(2,882)	(2,657)
Dependent mean	42.33	11.88	7,853	3,192	11,328
Number of workers			10,894		
Two years after application					
Processing times	0.960	-1.172*	222*	-604**	-386*
	(0.595)	(0.520)	(129)	(249)	(223)
Prepayment	11.697	25.177*	-583	12,271*	11,909**
	(14.716)	(14.679)	(3,314)	(6,551)	(5,715)
Dependent mean	73.29	28.61	13,919	9,284	23,774
Number of workers			10,553		

Note: Results of IV models with two endogenous variables (application processing times and prepayments) and two instrumental variables (caseworker speed and caseworker prepayment grant rate). Time in welfare and work are measured in weeks. All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Standard errors in parentheses are robust and clustered at the caseworker level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table C.7: Effects of prepayments on cumulative outcomes among awarded applicants - instrumental variable estimates

Dependent variable:	Welfare receipt	Work	Welfare benefits	Earnings	Total income
	(1)	(2)	(3)	(4)	(5)
A. ALL AWARDED:					
One year after application					
Estimate	-1.739	6.840	-36	2,771*	2,880*
(s.e.)	(3.906)	(4.542)	(1,120)	(1,623)	(1,566)
Dependent mean	42.10	12.52	7,837	3,501	11,655
Number of workers			12,820		
Two years after application					
Estimate	-4.255	15.185	189	6,358	6,513*
(s.e.)	(9.623)	(9.486)	(2,110)	(3,897)	(3,637)
Dependent mean	72.55	29.90	13,825	9,984	24,424
Number of workers			12,418		
B. AWARDED AFTER 4 WEEKS:					
One year after application					
Estimate	-2.118	9.488*	264	4,712**	5,272**
(s.e.)	(4.891)	(5.682)	(1,291)	(2,175)	(2,048)
Dependent mean	42.33	11.88	7,853	3,192	11,328
Number of workers			10,894		
Two years after application					
Estimate	-7.046	4.500	492	9,345*	10,037**
(s.e.)	(12.088)	(12.090)	(2,794)	(5,249)	(4,560)
Dependent mean	73.29	28.61	13,919	9,284	23,774
Number of workers			10,553		

Note: Time in welfare and work are measured in weeks. All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Additionally, the regressions control for caseworker speed. Standard errors in parentheses are robust and clustered at the caseworker level. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table C.8: Effects of prepayments on cumulative outcomes after one year for different demographic groups – instrumental variable estimates

Dependent variable:	Welfare receipt	Work	Welfare benefits	Earnings	Total income
	(1)	(2)	(3)	(4)	(5)
A. GENDER:					
1. Female					
Estimate	-2.675	4.627	-126	1,632	1,237
(s.e.)	(6.117)	(6.526)	(1,544)	(2,167)	(1,764)
Dependent mean	42.38	12.97	7,837	3,252	11,391
Number of workers			6,189		
2. Male					
Estimate	0.199	8.984	19	4,092	4,681*
(s.e.)	(6.061)	(6.254)	(1,713)	(2,619)	(2,697)
Dependent mean	41.84	12.09	7,836	3,733	11,903
Number of workers			6,631		
B. AGE:					
1. Aged 27-35					
Estimate	0.301	7.152	682	1,576	2,430
(s.e.)	(6.108)	(7.234)	(1,653)	(2,678)	(2,553)
Dependent mean	41.11	13.75	7,535	3,965	11,777
Number of workers			6,232		
2. Aged 36-49					
Estimate	-2.826	7.364	-587	3,820*	3,332*
(s.e.)	(4.993)	(6.464)	(1,362)	(2,116)	(1,992)
Dependent mean	43.14	11.22	8,156	3,009	11,527
Number of workers			5,232		
C. NATIONALITY:					
1. Native					
Estimate	-11.490*	14.728*	-2.664	7,049**	4,632*
(s.e.)	(6.614)	(7.925)	(1,676)	(3,132)	(2,446)
Dependent mean	41.27	14.55	7,443	4,360	12,175
Number of workers			2,803		
2. First generation migrant					
Estimate	0.337	1.779	350	875	1,349
(s.e.)	(6.108)	(7.118)	(1,858)	(2,465)	(2,327)
Dependent mean	42.52	11.58	8,111	2,977	11,395
Number of workers			6,877		
3. Second generation migrant					
Estimate	9.954	0.872	3,852	-606	2,914
(s.e.)	(9.875)	(10.435)	(2,595)	(4,691)	(4,070)
Dependent mean	41.90	12.75	7,587	3,879	11,762
Number of workers			3,140		
D. WORK:					
1. Employed in preceding year					
Estimate	1.430	8.239	432	4,036	4,463*
(s.e.)	(5.709)	(7.830)	(1,740)	(2,742)	(2,338)
Dependent mean	39.76	21.04	6,951	5,689	13,079
Number of workers			5,625		
2. Not employed in preceding year					
Estimate	-5.833	6.628	-730	2,077	1,629
(s.e.)	(5.430)	(4.865)	(1,447)	(1,932)	(2,009)
Dependent mean	43.92	5.860	8,529	1,789	10,543
Number of workers			7,195		

Note: For efficiency reasons, we estimate a model specification with one endogenous variable (receiving a prepayment) while controlling for caseworker speed, similar to Table C.7. All regressions include controls for age dummies, gender, nationality, labor market history, UI exhaustion, and team fixed effects interacted with year fixed effects. Time in welfare and work are measured in weeks. Total income includes benefits from welfare, UI and DI, earnings and income from self-employment. Standard errors in parentheses are robust and clustered at the caseworker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$