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A fast track for timely unemployment benefits: Impacts on liquidity constrained households from administrative data *

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Abstract

This study evaluates the effectiveness of a program introduced in Norway during the COVID-19 pandemic that provided the option to apply for advance benefit payments to mitigate the impact of delays in the processing of unemployment insurance (UI) claims. We examine whether access to timely UI transfers effectively targeted the intended groups or instead attracted mainly financially literate households. By combining individual application data, demographic information, imputed consumption, and household balance sheet data, we estimate that the vast majority of financially constrained households avoided temporary consumption shocks through advance payment. According to our estimates, the median constrained applicant avoided consumption postponement of 31 percent, comparable to a household welfare gain of 5 percent, concentrated among single adult households.

Keywords: unemployment insurance, liquidity constraint, consumption smoothing, policy evaluation, COVID-19
JEL codes: E21, I38, J65

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1 Introduction

Social transfer programs serve as a financial safety net, insuring individuals against negative income shocks such as unemployment. In studies of unemployment insurance (UI) design, the welfare gains are determined by households' willingness to postpone consumption during employment periods for receiving means to keep consumption if becoming unemployed. The gains from UI, affected by preferences and risk of unemployment, need to be weighted against adverse effects on job search incentives (Baily, 1978; Chetty, 2006, 2008). While the UI literature studies the impacts of replacement rates (East and Kuka, 2015) and duration of entitlement (Ganong and Noel, 2019) to evaluate its consumption smoothing benefits (see Schmieder and Von Wachter, 2016, for the overview of literature), this article focuses on a program designed to mitigate temporary fluctuations in household consumption due to delayed transfers of UI benefits.

In the face of negative income shocks, liquidity-constrained households (hand-to-mouth) are particularly vulnerable, exposed to consumption volatility and more dependent on the social safety net (Zeldes, 1989; Ludvigson, 1999; Dogra and Gorbachev, 2016). Therefore, the welfare gains of an UI institution also depend on its prompt benefit delivery to avoid an additional (temporary) drop in consumption for constrained households. Timely transfers are particularly important when delays have tangible repercussions, such as suboptimal investment decisions (Duflo et al., 2011) and disruption in the planned use of future income (Bazzi et al., 2015; Giné et al., 2018). When large-scale events such as the COVID-19 pandemic reduce the market income of many households, administrative delays are almost inevitable. Therefore, the welfare gain from policies that effectively limit such delays can be substantial. It is particularly important that such a program actually reaches families in need, as the literature on non-take-up of transfers shows that people often refrain from accessing the assistance they are entitled to, despite its availability (see, for example Moffitt, 1983; Duclos, 1995; Kleven and Kopczuk, 2011; Hupkau and Maniquet, 2018, among others).

We examine a program introduced in Norway during the initial phase of the COVID-19 pandemic to limit the impacts of the inevitable delays in the processing of unemployment insurance (UI) claims. In a quick response to anticipated delays of several months, on 31 March, the Norwegian Labour and Welfare Administration (NAV) offered claimants who had already filed for UI a fast track, or more precisely, an opportunity to apply for an in-advance payment (*forskudd*). Motivation was to secure income for laid off and unemployed workers who had to wait an unusually long time[1] for a response to their UI claim. The application was easy to file, followed by an automated eligibility check, and the advance payment on the estimated UI benefits was in the applicant's bank account the next working day. Advance payment did not affect total UI benefits received, just timing. Applicants received the UI flow sooner than nonapplicants who received retroactive benefits for the time they spent waiting.

This article studies whether the program alleviated any effects of liquidity constraints on consumption smoothing. Our focus is on delayed benefits, and we do not cover effects of the UI itself. Since the welfare gain of timely social insurance transfers arises from the avoidance of transitory shocks to consumption, we document the reach of the program and to what extent it effectively targeted the intended groups or whether it predominantly attracted affluent, financially literate households. We combine data on individual applications among eligible UI claimants with detailed register data on demographics and household balance sheets. When examining the impact on households that applied, we use household income data to impute counterfactual consumption over time in the absence of the program. Although administrative data miss actual consumption flows, they offer the advantages of complete data without attrition, other sources of survey bias, and accurate household identifiers, which enable us to correctly aggregate to the relevant decision unit. Finally, we estimate the welfare gains of avoiding consumption fluctuations based on a simplified theoretical framework and compare with estimated program costs.

In line with the non-take-up of welfare programs literature, we find that half of eligible UI claimants applied for advance payment. We also show that the initial unemployment shock during the pandemic hit many families with substantial financial resources, making

[1]For example, the surge in unemployment insurance claims in the US — with pre-pandemic figures of weekly 200,000 claims on average to an astonishing 6 million claims in late March and early April 2020 — extended the processing times of applications from roughly 2 weeks to 6-7 weeks (U.S. Bureau of Labor Statistics, 2021).

consumption smoothing easy without advance payments. More importantly, households with few liquid assets were much more likely to apply. Based on bank account balance data for households and (ex-post) UI post-tax benefits over the first 10 weeks, we estimate that one in four eligible UI claimants lived in constrained households where the delayed UI exceeded the initial bank deposits. The application rate of the constrained households was 20 pp higher than among the non-constrained. According to theoretical predictions, a household is more likely to apply for social assistance when the predicted benefits are larger and last longer (Anderson and Meyer, 1997; Card and Levine, 2000) and less likely when the application process is costly (Duclos, 1995; Kleven and Kopczuk, 2011) and stigmatizing (Moffitt, 1983; Contini and Richiardi, 2012; Kühner and Chou, 2023). We find that a large group of eligible individuals do not take advantage of the opportunity to receive timely support, even when both application and stigma costs are almost non-existent, highlighting the importance of understanding the factors behind such behavior and the need for alternative explanations. When we expand the financial capacity to include liquid assets of the family dynasty (parents and siblings), we find that the probability of application decreases in bank deposits of the dynasty, aligned with the findings in the literature on informal insurance within familial and social networks (Kaplan, 2012; McGarry, 2016; Edwards and Wenger, 2019; Andersen et al., 2020). The probability of an application is decreasing in educational attainment but higher for immigrants and large families. While the gender difference is small, ordinary unemployed were less likely to apply than those on a furlough.

With the program, liquidity-constrained applicants could avoid temporary shocks to consumption by means of advance payments. We argue that the major welfare gain comes from the consumption smoothing, or the avoided misallocation of consumption, provided by the program. Our estimates of improved consumption smoothing are based on an imputed counterfactual for each of the 30k households (17% of the sample) which applied for advance payment. Among constrained applicants, the median postponement of consumption in the absence of the program is estimated to be 31% of the smooth consumption level. Based on log-linear utility, we estimate household's willingness to pay for smooth consumption and find a median of 5% of consumption for the constrained applicants. We find that the benefits of the program are concentrated among single adults who applied with a median willingness to pay of 10% compared to a median of 2% for couples, reflecting that partners provide an important "safety net".

Program costs include labor input to the construction of the web portal for the application process, to code eligibility checks, and to set up payment mechanisms. The program was built on existing automatic infrastructure and was operational after a week with the effort of a handful of programmers and designers. Since the advance program algorithm estimated eligibility from administrative earnings records with some measurement error, substantial resources were needed to handle the repayment of excess advance benefit payments. Still, estimated costs are well below the welfare gains among households enabled to smooth consumption.

Our paper makes several contributions. First, we provide evidence on the effectiveness of the advance payment program. In this regard, we contribute to the growing literature on the diverse effects of COVID-19 and the evaluation of policies aimed at stemming it, in particular, transfer programs aimed at preserving household consumption.[2] Using the COVID-19 pandemic as a lens, our research extends its reach to the examination of the various impacts of external shocks and contributes to a broader understanding of the effectiveness of welfare programs. Our findings offer insight into the design and implementation of social insurance programs, including who benefits the most from such interventions and how different demographic groups respond. We illustrate that policy responses based on existing infrastructure can be implemented quickly at low costs with substantial gains for vulnerable families, presumably valuable to policymakers looking for evidence-based strategies to strengthen social welfare systems.

Second, our evidence on the welfare implications of delays in social transfer disbursement contributes to a better understanding of the importance of timely benefit delivery — area that has remained relatively unexplored in the existing literature. While previous

[2] Kubota et al. (2021) and Feldman and Heffetz (2022) evaluate the universal one-time cash transfer program in Japan and Israel, respectively. Including in-kind transfers, such as the digital coupon program in China (Liu et al., 2021) and vouchers in South Korea (Kim and Lee, 2021).

studies have examined programs designed to supplement existing income sources, we focus on a program that prevents *delays* in unemployment benefit payments.[3] We are not aware of any study that estimates the welfare loss of delayed benefits. This, additionally, allows us to extend the literature on sources of non-take-up of welfare benefits by speculating on alternative factors such as family support and financial literacy.[4] A related study on the US' 'retention policy' (Xie, 2019) demonstrates that postponing unemployment benefit claims to future unemployment spells might be optimal and increase the job finding rate. In our case, the program is unlikely to have behavioral effects on job search, in part because the majority of eligible applicants are temporarily unemployed (on a furlough) with a recall rate close to one.

Our study is interesting in light of recent research that emphasizes a high sensitivity of consumption to cash-in-hand and a prevalence of present-biased and myopic behavior of consumers. Empirical evidence shows that some consumers fail to save from positive temporary income shocks in anticipation of subsequent negative income shocks (Ganong and Noel, 2019; Gerard and Naritomi, 2021), even in the absence of delays in UI payments. However, when confronted with delays - periods of immediate drop in labor income for an unpredictable duration - the benefits from timely UI assistance are expected to be more pronounced.

This distinction is crucial as it aligns with the unique circumstances of the COVID-19 pandemic, allowing us to shift the focus away from the typical concerns surrounding the costs of job search effort and associated moral hazard when evaluating the gains of the program, which are primary concerns in the UI literature. It also helps us to focus solely on delays in the transfer and disregard the impact of the initial income shock.

[3] Bazzi et al. (2015) study the delays in an unconditional cash transfer program in Indonesia in shaping the consumption behavior of recipients. They report that while timely transfer does not alter consumption, delays in transfer significantly reduce expenditure. Brune et al. (2017) in an experiment on Malawi households conclude that 1-8 days delay in cash transfer has no impact on spending.

[4] The empirical evidence is dominated by factors such as the level and duration of benefit (Anderson and Meyer, 1997; Card and Levine, 2000), stigma (Contini and Richiardi, 2012; Kühner and Chou, 2023), and application cost (Duclos, 1995), for example, its complexity and time spent (Ebenstein and Stange, 2010; Kleven and Kopczuk, 2011) to explain the take-up rate. Unlike existing case studies, unemployment insurance is often mandated and universal, hence viewed as less stigmatizing, i.e. have higher take-up rates compared to social assistance programs (Hernanz et al., 2004), and its level and duration are determined by conditions of past employment, rather than financial need, which requires an alternative perspective on benefit utilization behavior.

2 The fast track UI payment program

In Norway, the COVID-19 crisis hit the labor market on March 12, 2020, due to strict regulations on social distancing and lockdown. The immediate and massive drop in market activity led to an unprecedented increase in unemployment insurance (UI) claims, with the unemployment rate hitting a record high level of 10.7%.[5] The UI is administered by the Norwegian Labour and Welfare Administration (NAV).

Before COVID, UI eligibility required a loss of 50 percent or more of their total working hours due to temporary or permanent layoff, and earnings of least 1.5 G (1G=101,351 NOK (around 10,782 USD) by March 2020) during the last 12 months to qualify for 52 weeks of UI.[6] In response to the COVID shock, within days the Norwegian parliament temporarily expanded the unemployment insurance program with higher replacement rates, extended maximum duration, and introduced lighter eligibility requirements. More specifically, the minimum income threshold was reduced by half (to 0.75G) and the reduction in working hours was increased to 40% for broader coverage. For people close to the maximum period, the duration was extended until the end of June (later extended to the end of October). For temporary unemployed, the maximum period was extended from 26 to 52 weeks. Finally, the replacement rate was increased from 64% to 80% for previous earnings below 3G.[7] To complete the UI claim process digitally, it takes around 20-30 minutes, including time to provide necessary personal information, details of employment history, and other relevant documentation. The information must be given in Norwegian, requiring proficiency in the language or assistance from a translator if necessary. NAV provides guidance or assistance to applicants who encounter language barriers to ensure that they understand and fulfill application requirements effectively. During the unemployment spell, an 'employment status form' ('meldekort') must be filed bi-weekly, certifying their job-seeking efforts and hours worked if any.

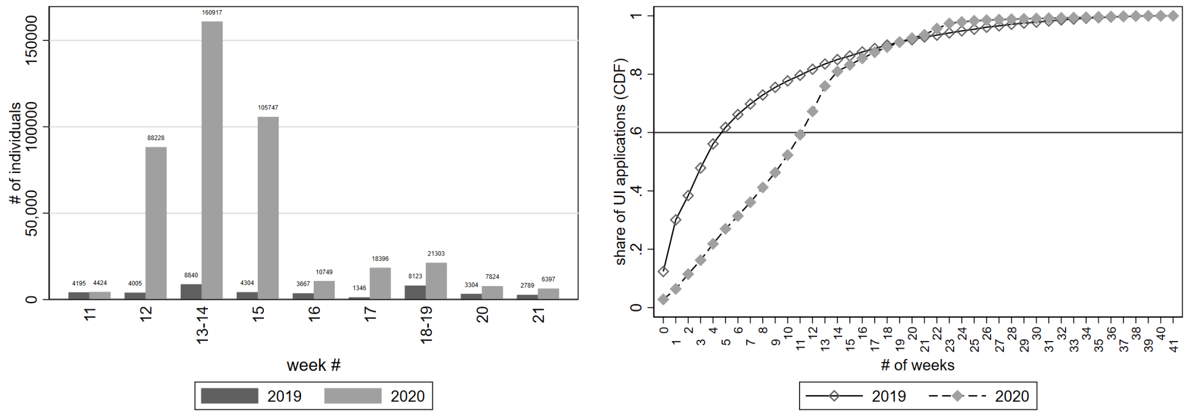
[5] *Source:* https://www.nav.no/no/nav-og-samfunn/statistikk/arbeidssokere-og-stillinger-statistikk/relatert-informasjon/arkiv-hovedtall-om-arbeidsmarkedet-2020

[6] With earnings about 3G, where G is the basic amount in the social security system, the maximum duration is 104 weeks. The average exchange rate for 2020 was 1 USD = 9.4 NOK.

[7] See Heggebø and Pedersen (2023) for more details on temporary changes in unemployment benefits during COVID-19.

In weeks 12-15 of 2020, more than 360,000 individuals[8] filed for unemployment insurance (Figure 1a). About 9 in 10 claimants were temporarily laid off (on furlough) and many were partially unemployed because they worked reduced work hours.

Figure 1: **Unemployment inflow and UI handling time.**



(a) Unemployment inflow

(b) Handling time of ordinary UI claims

Notes: Panel (a) depicts the inflow into unemployment from the start of the lockdown (March 12) — week 11. Panel (b) plots the cumulative distribution of processed applications for unemployment insurance. Based on the authors' calculation.

NAV was not rigged to handle this dramatic increase in demand, and early announced that it could take several months before a claimant had their case handled and ordinary payments were executed. Under these perspectives, the government quickly instructed NAV to install a temporary program with advance payments for UI claimants. It was adopted and implemented on the 30 March 2020 and ran until June 2021. In retrospect, the handling time of ordinary UI claims increased considerably. While more than half of the claims were processed within four weeks at the same time in 2019, less than two in ten had their case decided within the same period in 2020 (Figure 1b).

The program offered an advance payment to UI claimants while waiting to receive insurance based on confirmation that the claim was accepted. Advance payment did require a separate application (Bakken and Vidal-Gil, 2020) which had to be renewed every month. A new Web portal was established at www.nav.no and the application was

[8]Note that individuals who claimed UI, but did not meet the eligibility criteria for receiving the transfer are excluded from our sample.

filed digitally and required an electronic ID.[9] The eligibility criteria for advance payment were that you stayed in Norway as a member of the national insurance system, had filed your UI claim, registered as a job seeker, and aged 18-66. The advance payment was just slightly below the UI benefit; 60% of previous earnings up to a threshold of about 600,000 NOK. According to standard practice for UI transfers, about 25% of the advance amount was withheld for income taxation. The accumulated advance payment was deducted from the sum of unemployment benefit up to the date when the decision of the UI claim was made. If the advance payment receiver returned to work early, she/he had to pay pack what exceeded the UI. For eligible UI claimants, the advance payment did not affect the total benefits received, just the timing. The advance payment applicants began receiving a monthly flow benefit sooner, and the non-applicants received retroactive benefits for the time they spent waiting.

The advance payment application form was easy to complete in a couple of minutes without any information that required effort from the applicant (Screenshots of the application process are in Figure A.2). Information on the core eligibility criterion — past earnings — was collected from administrative registers. The processing time for advances on unemployment benefits was just one day and the advance was typically paid the following working day, unless the payment system was missing necessary information such as the bank account number or address of the applicant.

The advance payment program contributed significantly to the transfer of UI to households during the initial phase of the pandemic. Figure 2a shows that about half of the total UI benefits paid during the first six weeks were advance payments.

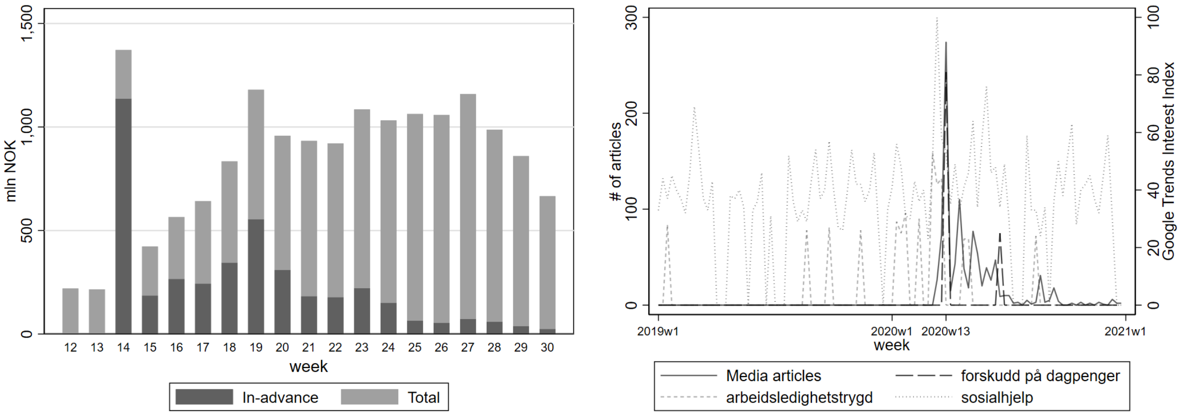
Due to extensive media coverage and NAV announcements on nav.no, in both Norwegian and English, we believe that the program was salient to most UI claimants. A text message was sent to about 350,000 UI claimants on March 30 and April 3, inform-

[9]The system was set up in three days by using and developing the pre-existing infrastructure and microservices available at NAV. In particular, a new infrastructure was set up that includes (1) a user-friendly application form accessible behind a secure login with BankID; (2) a robust *Kotlin* backend responsible for verifying eligibility for UI and calculating the corresponding amount; (3) a database to systematically store the results of the application process; (4) a CSV generator designed to facilitate payments disbursement. *Source:* https://www.kode24.no/kodenytt/slik-koda-nav-ny-dagpenge-losning-pa-tre-dager/72331871

ing them about the opportunity to apply for advance payment (internal memo in NAV included in the Appendix, Figure A.3). A quick search on the local media coverage using *Atekst* — a digital archive of newspapers and periodicals in Norway — reveals the program's prominent presence, with a noteworthy 985 mentions in both local newspapers and web publications. Similarly, using Google Trends, an online tool that allows users to analyze and visualize the search interest and popularity of particular keywords on the Google search engine, we found substantial interest in "forskudd på dagpenger" (advance unemployment benefits) during the launch of the program.[10] Weekly data on the number of related media articles and the Google Trends Interest Index on the topic are depicted in Figure 2b. Note that while the figure provides some valuable insights on program awareness trends, it does not reveal any information on individual/household decision-making process, therefore providing only suggestive and not conclusive evidence on program take-up.

[10]Google Trends Index has limitations due to its reliance on relative comparison terms, impacting search interest trends interpretation. It is crucial to choose related comparison terms for meaningful insights, which should ideally reflect concepts or topics closely aligned with the primary query of interest. For example, using overly general terms like "COVID-19" or "lockdown" for comparison may not yield meaningful insight, as the search interest for such broad topics will overshadow more specific queries like "forskudd på dagpenger". We believe that terms such as "arbeidsledighetstrygd" (unemployment benefit) and "sosialhjelp" (social assistance) are more relevant in this context.

Figure 2: **Program Salience.**



(a) Total UI paid out by week in 2020

(b) Media Coverage

Notes: Panel (a): Source: NAV. Total UI and UI in advance paid out during the corona-crisis. In million Norwegian kroner (NOK). Panel (b): The left-hand axis (solid line) depicts the number of articles in both digital and paper news outlets including radio and TV mentions in *Atekst* — a media monitoring and news database service based in Norway. The following query was used [“forskudd dagpenger” OR “forskudd på dagpenger” OR “dagpengeforskudd” OR “forskudd ledighetstrygd” OR “forskudd på ledighetstrygd” OR “forskudd arbeidsløshetstrygd” OR “forskudd påarbeidsløshetstrygd” OR “forskudd AND dagpenger” OR “forskudd AND arbeidsledighetstrygd” OR “forskudd AND arbeidsløshetstrygd”] to ensure that all “advance unemployment benefit” related keywords are captured within one search. The right-hand axis (dashed lines) depicts the Google Trends Interest Index for the “forskudd på dagpenger” (advance on unemployment benefits, long dash) search query for Norway relative to more general terms; “arbeidsledighetstrygd” (unemployment benefit) and “sosialhjelp” (social assistance). Google Trends does not provide the number of searches made for a keyword/phrase. It uses a scaled index from 0 to 100 where the highest point on the scale represents the peak of search interest for a specified time and location.

3 Data

The program ran from March 2020 to June 2021. Since most of the applications were submitted during the first months, we include applications during March-May 2020 (71% of the total). The sample is restricted to eligible UI claimants who (finally) received UI. The unemployment shock did not only affect families with limited economic resources. In Figure 3 panel (a), we compare the distribution of household bank deposits in the sample of UI recipients to that of the total population. Bank deposit information is from annual tax reports by the end of 2019, considered accurate due to the extensive coverage of third-party reporting by financial institutions. As expected, the deposit distribution for UI claimants is to the left of the total adult population, but not much. The median deposits of the UI sample is 104,812 NOK, compared to 113,867 NOK for the total population.

Although the application had to be renewed every month, we define one record per person and the binary outcome *applied for advance payment* is yes if the UI claimant applied for advance payment at least once. We excluded applications from individuals who did not qualify for UI and were required to repay advance payments. We also dropped applications rejected on the basis of some other eligibility criteria. Details on sample construction are given in Appendix B.

Since the handling time was unknown at the time of filing, we use an expected handling time of 10 weeks for all households, close to the average observed in the data. We compare the household-level UI benefits for the first 10 weeks with the bank deposits. In Figure 3 panel (b), we show that the median UI benefit is 33,500 NOK and 74% of the UI claimants' households had more than (three times) that amount in deposits.

In line with the literature, we do not observe whether a household is liquidity constrained or not. Earlier studies use various definitions based on liquid wealth, often compared with income (as a proxy for expenditures). Other measures include credit card limits or utilization, savings amount, debt ratio, age, or home ownership (mortgage), depending on the nature of the data and its availability. We define the household as liquidity constrained if initial bank deposits were less than the actual ten weeks of UI benefits net of tax deductions. Households may appear to have limited liquidity, but it is common to have flexible credit, often with the value of the house as collateral. On this background, we assume that households with a gross wealth more than twice its debt have easy access to credit, and therefore we re-classify them as non-constrained, even if their bank deposits are below the UI benefits. While the estimated share of constrained households is context specific, our 24% aligns fairly well with the shares reported in the existing literature. For example, Hajivassiliou and Ioannides (2007) identified 40-60% of unemployed individuals as constrained (defined as total asset income relative to average income over last two periods less than 1/6) from Panel Study of Income Dynamics (PSID), while Kaplan and Violante (2014) estimates (no liquid wealth) identify 17-35% of households as 'hand-to-mouth' in the US. Zeldes (1989) identify 15-30% of the households in PSID as financially constrained defined as households with small (almost zero) wealth or savings below two months of income, while Aguiar et al. (2023) classify 17% for the sample in later years.

Our administrative data contain the crucial household identifier, which enables us to sum wealth and income for couples who typically pool resources. However, our information set is not perfect. We do not have information on access to credit. The utilization of backdated account information, specifically bank statements as of the end of 2019, indicates that our assessment of liquidity constraint may contain errors. Even, if bank account data at the time the program commenced (March 2020) would have been a more accurate representation of liquidity, bank deposits are likely to be quite stable over a 2-3 month period.

In Figure 3 panel (c), we display the deposit-benefit ratio (R) distribution for the households of UI claimants (right scale and winzorized at ten). While about one in four households had less deposits than what they received in after-tax benefits for the first 10 weeks, the median deposit/benefit ratio is close to three. In the same panel, we also report the application rate by grouped deposit-benefit ratio (left scale). This association is strongly negative for low deposits, but then it flattens. Among the wealthiest half of the unemployed households, four out of ten applied for advance payment. The application rate among the least affluent with $R < 1$, is two-thirds (67%).

Households are often part of a family dynasty that offers transfer and/or liquidity to smooth consumption (McGarry, 2016; Andersen et al., 2020). We do not observe actual transfers from extended family members, but their bank deposits provide a proxy for the safety net they may offer. Our family dynasty insurance indicator is based on the sum of bank deposits of the parents of adult members of the family. In the last panel of Figure 3, we report the total parental deposit-benefit ratio (RP). The parental ratio is higher than for the own deposits, partly reflecting that we sum up to four family members. Parents are also older and wealthier. As for the own deposits, the application rate is decreasing in parental deposits. However, it may simply mirror the own deposits since wealth is correlated across generations (Charles and Hurst, 2003).

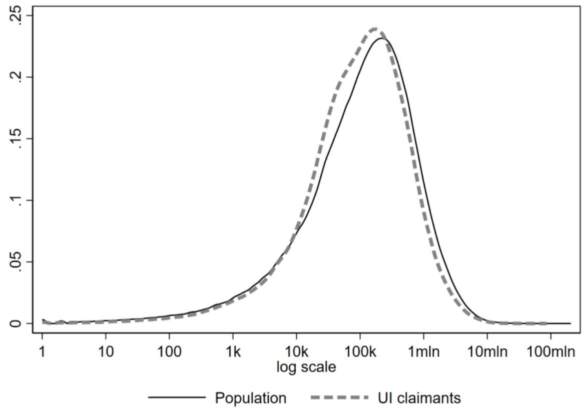
The sample of approximately 178k individuals is described in Table 1 and the first row reports three main features. First, one in two (51.2%) applied for advance payments. Second, close to one in four (24.4%) of the UI claimants lived in liquidity-constrained households. Finally, constrained UI claimants were more likely to apply with a difference of 22.0 percentage points compared to those with sufficient assets to smooth consumption.

Column (1) in Table 1 reports the mean of individual and household characteristics. Most are male (53.6%), mainly due to the high proportion of women in the public sector, which did not have any layoffs during the pandemic. We also see that five out of six were temporarily laid off (on furlough). Immigrants, young people, and low-education workers are groups disproportionately hit by the first labor market shock (Bratsberg et al., 2010; Dustmann et al., 2010; Hoynes et al., 2012) and this is reflected in the sample shares. We do not have specific information on financial literacy, but educational qualifications in fields of study such as economics, business and administration, and mathematics and statistics at the high school and tertiary education levels are used as a proxy.[11]

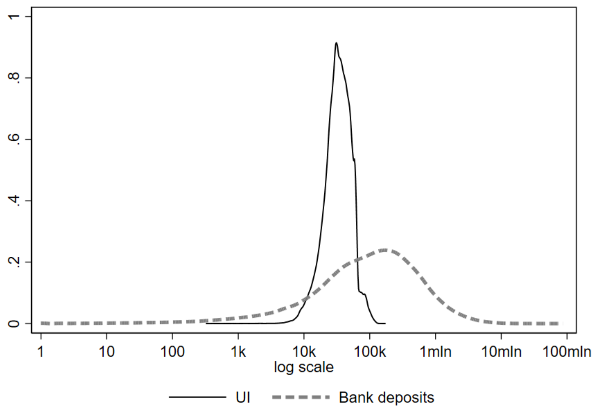
In column (2), we report how the application rate varies between groups. Workers on a furlough were more likely to apply. We find a gender difference of about 3 pp in favor of men. Divorced and single adults are more likely to apply than married adults. Many children, immigrant status, and low education go hand in hand with higher application rates. Older employees are less likely to apply, presumably because they are wealthier.

[11] Similar to Guiso and Jappelli (2005); Christiansen et al. (2008).

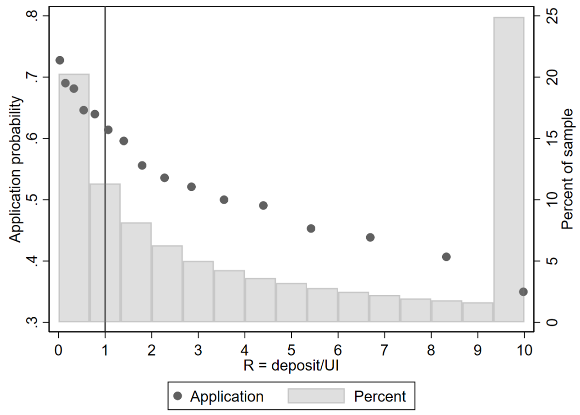
Figure 3: **UI Benefits, Bank Deposits and Application.**



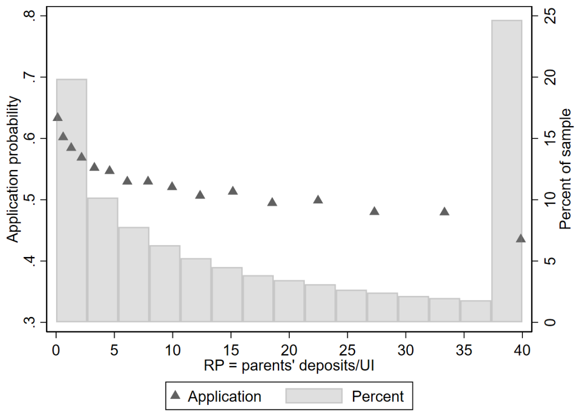
(a) Bank deposits



(b) Bank deposits and UI benefits



(c) Own liquidity and application



(d) Parental liquidity and application

Notes: Panel (a) plots the distribution of household bank deposits by 31 Dec 2019, for our UI claimants sample and all Norwegians aged 15 to 66. Panel (b) depicts the distribution of post-tax unemployment benefits for the first 10 weeks of unemployment and household bank deposits, both for the UI sample. Panel (c) plots the distribution of the household deposit-benefit ratio (R, right scale) and the in-advance application probability by R-group (left scale). Panel (d) plots the distribution of the household's parental deposit-benefit ratio (RP) - parents' bank deposits over household unemployment benefits - used as a proxy for family dynasty credit and probability of applications over RP.

In column (3), we report shares of liquidity constrained households. About one in four of the unemployed lived in constrained households. Ordinary unemployed workers are more likely to be constrained than furloughed workers. Single persons, immigrants, young, least educated and those with the least affluent parents were more likely to meet a liquidity constraint if they had to wait until their claim was handled.

In the final column of Table 1, we report the difference in application rate between constrained and non-constrained UI claimants, by characteristics. It is striking that the excess application rate among the constrained is fairly constant across groups. For most observable groups, the excess application probability for the constrained is around 20 pp. This indicates that our empirical model can be specified without allowing for extensive interaction terms.

4 Theoretical motivation

A UI claimant files an advance payment application for different reasons. A transfer is better today than tomorrow. More importantly, households without access to sufficient liquid assets have an incentive to apply to avoid constraints on optimal consumption smoothing.

The household receives after-tax income from other sources per week (Y) and is entitled to weekly unemployment benefits ($UI = aWU$) if unemployed, where a is the after-tax replacement rate, W is hourly pay, and U denotes hours of unemployment. We assume that all unemployed claim their benefits, because benefits are relatively high and can be claimed at a low cost.[12]

Due to the massive inflow into unemployment, the handling time of H weeks before the claim is accepted increased substantially (Figure 1). Without any advance payment, unemployed individuals do not start receiving benefits before time H, at which point they

[12]Evidence from US, UK, and Canada suggest that only 60 to 80 percent of eligible individuals actually claim their UI benefits, partly explained by short expected unemployment spells and low replacement rates (Hernanz et al., 2004). In light of expansions in both coverage and increased replacement rates (up to 0.8) during the COVID-19 pandemic, we argue that non-take-up of UI is of minor importance. Moreover, as argued by Kopczuk and Pop-Eleches (2007) the electronic application submission eases the process and increases program participation.

Table 1: **Descriptive statistics.**

	All	**Applied**	**Liquidity constrained**	
		(%)	(%)	Application gap(pp)
	(1)	(2)	(3)	(4)
All	178,537	51.23	24.43	22.03
UI eligibility				
Furlough	83.99	53.89	23.06	24.00
Unemployed	16.01	37.29	31.57	19.64
Gender				
Male	53.61	52.60	28.19	22.27
Female	46.39	49.65	20.08	21.37
Marital status				
Single	52.75	51.55	27.97	21.77
Married	36.16	49.39	18.08	22.84
Widowed	0.53	45.36	15.51	25.22
Divorced	8.93	57.31	26.52	21.61
N/A	1.63	50.48	42.21	19.30
Number of family members				
1	25.01	54.69	37.55	22.20
2	26.98	49.29	17.88	23.90
3	20.04	49.94	21.18	20.59
4	20.18	50.12	19.32	19.92
5 and more	7.79	53.06	26.56	21.86
Number of children, age below 17				
None	61.89	50.36	26.51	23.31
1	17.38	52.45	22.13	19.15
2	15.84	52.04	19.09	20.30
3 and more	4.89	55.29	23.44	23.90
Immigrant background				
Immigrant	26.80	54.98	34.58	18.83
Native	73.20	49.86	20.71	23.18
Years of age				
Below 30	27.84	51.83	31.48	19.15
30-39	26.15	54.02	26.43	20.90
40-49	21.62	53.44	23.05	22.03
Above 49	24.38	45.61	15.44	27.20
Education				
Less than high-school	26.80	56.25	34.28	22.00
High-school	38.51	50.72	23.57	20.75
Vocational	3.46	50.45	17.00	21.52
Bachelors	21.47	47.89	16.25	21.25
Masters and PhD	7.04	43.58	13.15	23.35
N/A	2.73	56.17	42.62	15.89
Financial education				
No	93.42	51.20	24.26	22.24
Self &/or partner, last 5yrs	4.88	49.92	18.17	21.44
Family dynasty insurance				
Low: RP $<$ 5	22.10	58.19	38.94	18.58
Medium: RP=[5,20]	23.39	51.76	21.35	19.81
High: RP $>$ 20	54.50	48.18	19.86	23.25

get a a one-time transfer of their delayed payments ($H * UI$). From then on, they receive a bi-weekly payment of $2UI$ until the unemployment spell ends. We ignore any uncertainty as to how long it would take before UI payments were transferred and assume that H is known. Even if H was not known, the variation was not large, since more than nine in ten had their UI claim decided within 20 weeks.[13]

The advance program offered access to a steady flow of unemployment benefits, even during the handling period, until the claim was actually checked out in detail and accepted. The advance program changed the timing of access to the UI without affecting the total amount of unemployment benefits (for a given spell).

To organize the discussion of application behavior and gains to households offered by the program, assume a household with initial assets, A_0, and a T weeks horizon. Here, T is considered fixed from the perspective of the household. This is a simplification, justified by our focus on the delay of UI and not on the effects of the UI replacement rates or maximum duration itself. In the empirical part on program gains, we discuss how T is defined.

Precautionary saving to smooth consumption in the event of a negative income shock (Carroll and Samwick, 1998; Lugilde et al., 2019) is an important reason to hold assets. A model with endogenous assets is beyond the ambition of this paper as we focus on the more limited impact of the delay rather than the UI parameters.Therefore, we ignore the smoothing of consumption related to the income shock itself and assume that the propensity to consume out of unemployment benefits is one for the whole period of T. Our simplifying assumptions are also motivated by an after-tax UI replacement rate of about 0.75 (or more), which means that the income shock is modest.[14] Consumption also depends on disposable income (Y) from other sources such as the spouse. As a logical consequence of exogenous assets, they are restored to their initial level by week T.

Denoting optimal (non-constrained) consumption during the unemployment period as

[13]In our empirical assessment of program gains we perform a robustness check where we randomly draw H from the realised distribution of H.

[14]Empirical evidence on the value of MPC varies substantially with the type of program and the available data; the average MPC reported is 0.35 (see Havranek and Sokolova, 2020, for extended meta-analysis of the evidence). Nevertheless, a more consistent finding is that financially constrained households have a higher MPC and it increases with unemployment rate (Kubota et al., 2021; Sokolova, 2023).

C^*, all households with $A_0 > H(C^* - Y)$ would like to draw on their assets to completely smooth consumption when their benefit payments are delayed. Although the average assets during the T periods are similar with and without smoothing, drawing on assets involves a (minor) cost in terms of foregone interest payments, which we ignore. If assets are large, handling time is short, and consumption covered by other income is large, perfect smoothing will be possible.

What is then the role of the program? It offers the opportunity to keep assets and interest payments unaffected. A non-constrained household would apply if the foregone interest payment exceeds the fixed non-pecuniary cost of applying. The foregone interest payments will depend on the expected duration, weekly UI benefits, and the interest rate. Even if the application costs are very small due to the efficient filing website, an interest rate close to zero suggests that the gains are small for households with sufficient liquid assets. However, even for households with assets expected to last, the uncertainty around the handling date created an incentive to apply for an advance allowance as a precautionary measure.

The constrained household is those for whom assets will dry out before the UI claim is handled, or $A_0 < H(C^* - Y)$. Without a program, the constrained household can use the available assets to smooth (constrained) consumption over H weeks, but not perfectly. It must postpone some consumption (P) during the H handling weeks, equal to $P/H = max(UI - A_0/H, 0)$, with a total weekly consumption of $C_H = Y + A_0/H = Y + UI - (UI - A_0/H) = C^* - P/H$. By this, we assume that the postponement is equally distributed over the H weeks. When the UI claim is handled, the household receives $UI \times H$ and allocates A_0 to restore the bank account. P is then left to increase consumption over the next $T - H$ weeks.

Our theoretical framework is not a rigorous model of optimizing agents. We simply compare two alternative consumption flows, where the postponed consumption in the absence of the program depends on the liquid assets and UI payments. We assume that preferences can be represented by the sum of weekly log consumption

$$U(C_H, C_{T-H}, H) = Hln(C_H) + (T-H)ln(C_{T-H}), \tag{1}$$

where C_H (C_{T-H}) is consumption before (after) the UI claim is handled by the administration.

Therefore, a household would apply if the utility with complete smoothing net of application costs exceeds the utility drawing on available assets without an advance payment

$$Tln(C^*) - \text{Application cost} \geq Hln(C^* - \frac{P}{H}) + (T-H)ln(C^* + \frac{P}{T-H}). \tag{2}$$

The gain of applying will depend on the postponement relative to the optimal consumption. If the household receives income from other sources (e.g. a spouse) or experiences part-time unemployment, the temporary consumption dip will be smaller in relative terms. Therefore, for single-adult-constrained households, delayed UI benefits have more severe effects on welfare than for two-adult households. Since the application costs were low, we predict that most well-informed constrained households would benefit from filing an application.

Then, why do we not observe that all constrained households applied? Ignoring the complication that we do not perfectly observe whether a household is constrained or not, limited/misperceived information about the program is an obvious candidate. Presumably, immigrants, less educated, with low financial literacy, are more likely to have missed the information campaign. Alternatively, social stigma is commonly referred to as a reason why people do not collect social insurance. Stigma costs, however, are less relevant in this context because the application process is kept confidential (online platform) and the unemployment shock affected everyone uniformly, without signaling out individual traits.

5 An empirical model of applications

We estimate standard linear probability models and start by including deposits and benefits, as well as personal controls (X_i) such as age, sex, family structure, immigrant background, and educational attainment:

$$Y_i = \alpha + \beta \ln(\text{Bank Deposits})_i + \lambda \ln(\text{UI Benefits})_i + \gamma X_i + \varepsilon_i. \tag{3}$$

Even if deposits and benefits have expected signs ($\beta < 0$ and $\lambda > 0$), this specification does not offer direct evidence on the role of liquidity constraints. Motivated by the theoretical discussion in Section 4, we introduce restrictions on how the combination of deposits and benefits affects the gain from advance payment. The size of the bank account (i.e., the deposit-benefit ratio) should not matter unless the household is constrained and must postpone consumption in the absence of advance payments. Our first check is whether the constrained household ($LC_i = 1$) is more likely to apply:

$$Y_i = \alpha + \theta \text{LC}_i + \gamma X_i + \eta_i, \tag{4}$$

where θ is expected to be positive.

When household consumption is largely sustained by alternative income sources, the incentive to apply is weaker. In our theoretical motivation, the gain from advance payment follows from the consumption postponement relative to the smooth consumption level, P/C:

$$Y_i = \alpha + \delta_1 (\frac{P}{C})_i + \delta_2 (\frac{ED}{C})_i + \gamma X_i + \mu_i, \tag{5}$$

P is postponed consumption, estimated as the sum of the weekly UI minus the bank deposits, divided by the number of handling weeks (fixed to ten). The smoothed consumption level (C) is imputed from annual disposable household income (divided by 52) for the last observation in our data (2019) assuming an average savings rate of 0.1. This assumption is based on evidence in the National Budget report of 2022[15], which reveals

[15] https://www.regjeringen.no/ chart 2.4, *Sources:* Statistics Norway and the Ministry of Finance.

a household savings ratio that fluctuates between 5-10 percent for the period 2002-2019, and spiked to around 20 percent at the beginning of the COVID lockdown, and dropped to around 15 percent by the end of that year. Micro-evidence indicates a median consumption rate of 95 percent of disposable income for the 1994-2012 in Norway (Fagereng and Halvorsen, 2017, Figure 6, p.80). Consumption is then calculated as a maximum of 90 percent of weekly family disposable income the previous year (2019) and after-tax household UI benefits.[16] To limit any measurement error, we use after-tax UI if previous income is low. We also include a measure of excess deposits (ED_i), defined as assets beyond what is needed to cover the delayed UI benefits.

From the theory, we predict $\delta_1 > 0$ and δ_2 to be (close to) zero. When adding the family dynasty insurance capacity to the empirical model, we expect that higher deposits among parents and siblings will be associated with a lower application rate. We also perform two robustness checks by including firm fixed effects (i.e. work colleague comparisons) and family fixed effects (i.e. siblings).

After all, we have no identification strategy that provides counterfactuals for constrained families if they had more money in the bank. Relying on a (rich) set of observables, the estimated coefficients for postponement, and excess deposits, we cannot claim causal interpretation without caveats. There are reasons to believe that the residuals in Equations 4 and 5 contain elements that affect saving and wealth, and also influence application behavior. The sign of this omitted variable bias is, however, ambiguous. Risk-averse households with precautionary savings will have risk preferences that make them more likely to apply for advance payment. This contributes to a negative correlation

[16] Previous studies mainly relied on consumption estimates from survey (Gruber, 1997) or transaction (Gerard and Naritomi, 2021) data. In contrast, we use administrative data to impute our consumption from disposable income. A strand of literature has developed to evaluate the accuracy and reliability of survey data in evaluating consumption patterns and deliberated on the accuracy of imputing consumption behavior from detailed administrative records, suggesting that such method offers a reliable alternative to traditional survey-based approach. Ideally, we would like to calculate consumption as income minus the change in wealth (Koijen et al., 2014), but this approach requires access to detailed household portfolio data and will only provide annual consumption estimates since wealth data are collected from the tax registry on a yearly basis. The measure has been adapted in multiple settings using Swedish (Kolsrud et al., 2018, 2020; Landais and Spinnewijn, 2021) and Norwegian (Kostøl and Mogstad, 2015; Fagereng and Halvorsen, 2017) data. Nevertheless, Fagereng and Halvorsen (2017) show that consumption (saving) estimates imputed from detailed registry data closely follow the estimates from the National accounts in Norway. Therefore, our consumption measure based on the assumption of 10 percent savings reported in National records is justifiable.

between consumption postponement and application probability which leads to a bias towards zero for variables that capture effects of liquidity constraints. On the other hand, if the program were less salient for constrained families, the "effect" of liquidity constraint would be upward biased.

6 Results

The estimated application models are shown in Table 2. All regressions also include individual characteristics such as gender, age, family structure, and education, and we find that the differences between groups are statistically significant but typically small. They are in line with the descriptives in Table 1, and we have relegated the complete set of coefficients to the appendix (Table A.1).

We confirm in column (1) that claimants with more money in the bank are less likely to apply and that higher UI benefits (in total for the first 10 weeks) are associated with a higher probability of filing an advance payment application. Claimants with financial education are more likely to apply.

More direct evidence on the role of liquidity constraint is given in column (2) where unemployed households with fewer deposits than 10 weeks of UI benefits are much more likely to apply for advance payments. The increase in application rate among constrained claimants is slightly reduced by including other characteristics, with a conditional differential close to 20 pp. We also introduce proxies for access to family network insurance in column (2), and find that more bank deposits among parents and siblings are associated with a lower application rate. A doubling of the deposits of parents or siblings predicts a reduction in the application probability of about 1 pp.

The theoretically motivated specification based on relative postponed consumption without advance payments (P/C) is shown in column (3). A marginal increase in P/C is associated with a significantly higher probability of application. The estimate implies that an increase in postponement from 1 to 31% predicts an increase in the application probability of 10 pp. In column (4), we split between the extensive and intensive margins of postponement, and the estimates suggest that both matter. Even among the constrained

Table 2: **Advance payment application.**

	(1)	(2)	(3)	(4)	(5)	(6)
ln(Deposits)	-0.0604***					
	(0.001)					
ln(UI Benefits)	0.0883***					
	(0.003)					
Liquidity constr (LC=1)		0.1975***		0.1462***	0.1445***	
		(0.003)		(0.004)	(0.004)	
Postponement (P/C)			0.3180***	0.0762***	0.0765***	
			(0.007)	(0.009)	(0.009)	
Excess Deposits (ED/C)			-0.0010***	-0.0009***	-0.0009***	
			(0.000)	(0.000)	(0.000)	
Postponement						
$[0.6, 1]$						0.2470***
						(0.005)
$[0.4, 0.6)$						0.2317***
						(0.005)
$[0.2, 0.4)$						0.2214***
						(0.004)
$(0, 0.2)$						0.2025***
						(0.004)
Excess Deposits						
$(1, 2)$						0.1672***
						(0.008)
$[2, 4)$						0.1469***
						(0.005)
$[4, 6)$						0.1302***
						(0.005)
Family Dynasty Insurance						
ln(deposits parents + inlaws)		-0.0118***	-0.0119***	-0.0101***	-0.0101***	-0.0097***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(deposits siblings)		-0.0138***	-0.0124***	-0.0116***	-0.0109***	-0.0114***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Financial literacy						
Financial education	0.0140**	0.0177***	0.0196***	0.0194***	0.0111*	0.0101*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Constant	0.5721***	0.5335***	0.5754***	0.5578***	0.4629***	0.4172***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.008)
Personal characteristics	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes
Occupation FE	No	No	No	No	Yes	Yes
Obs.	178537	178537	178537	178537	178537	178537
R^2	0.085	0.068	0.070	0.076	0.093	0.094

Notes: OLS estimates (std. err) of linear probability models. Reference group in (2) are non-constrained UI claimants and in (6) those with relative postponed consumption equal to zero and excess deposits higher than 6. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

individuals, larger postponement is associated with a higher probability of application.

In column (5), we confirm that the inclusion of occupation, industry, and county fixed effects does not matter. An exception is the financial literacy indicator, which is now borderline significant, presumably reflecting little variation in financial education with occupations and industries. Finally, in column (6), we test the linearity assumption and confirm a monotonically increasing "effect" of a potential postponement of household consumption.

The COVID-related unemployment shock disproportionately hit workers in industries affected by restrictions and lockdown. Temporary layoffs typically involved many coworkers. This enables us to study the effect of liquidity constraint among workplace colleagues by including firm fixed effects in the regression. Among 82.8% of the UI claimants had coworkers in the same firm who also claimed unemployment insurance.[17] By comparing colleagues, we account for shared unobserved factors that both affect application and potentially correlated with being liquidity constrained. An example is expected unemployment duration, which is likely to be similar for workers from the same firm. In Table 3, we report estimates with firm-fixed effects added in columns (1)-(3). The coefficients of interest are basically unaffected compared to the same specifications in Table 2. Thus, the associations between financial capacity to smooth consumption in the absence of an advance payment and application behavior are the same if we compare colleagues or workers in different firms.

Our second robustness check accounts for unobserved characteristics related to family background. In columns (4)-(6) of Table 3, we add family fixed effects defined by the mother ID of UI claimants. About 7.9 % of the UI claimants had siblings who also claimed unemployment insurance.[18] First, the higher application rate of liquidity-constrained households is very similar, whether we compare siblings or not. Second, the postponement coefficients in columns (5) and (6) are also very similar to what we identify in the entire sample in Table 2, but the association with excess deposit is smaller and insignificant. Overall, the association between financial capacity to smooth consumption and application behavior is similar if we compare siblings or households with different parental background.

[17] In Table A.2, we show that the sample of colleagues is representative as the OLS-estimates without firm fixed effects are almost identical to those in Table 2.

[18] In Table A.2, we show that the sample of siblings is fairly representative as the OLS-estimates are similar to those in Table 2. Note that we excluded the family dynasty insurance variables from the regression, as they are only defined for a household of two adults by the assets of in-law relatives

We expected access to family credit to be more important for constrained households, but when we test for interaction, we find no evidence of substitutability between the postponement predicted from the own deposits and the bank deposits of the parents (not included in the table). One might also expect that increased UI is particularly important if assets are low, but we find no clear evidence of any interaction effect between UI and bank deposits (not included in the paper).

In summary, we find that the program disproportionately recruited liquidity-constrained households. Even if we lack a waterproof strategy to identify this as causal, the evidence suggests that the constrained household applied more often *because* they would otherwise be forced to postpone consumption. Since welfare gains are limited to constrained households who applied for advance payment, our next step is to estimate the value of the avoided consumption postponement (or the counterfactual in the absence of the program) for this group.

7 Program gains and costs

According to our estimates, about 30,000 households avoided postponed consumption while waiting for their ordinary benefits to be transferred because of the program.[19] The counterfactual welfare loss of postponed consumption depends on its magnitude, whether household consumption was protected by other income sources (like the spouse not hit by unemployment) and on preferences (i.e., intertemporal consumption substitutability).

In Figure 4, we focus on constrained households, including non-applicants. The bars in panel (a) show the distribution of the relative postponed consumption in the absence of the program (P/C) explained in Section 5. The estimated counterfactual average (median) postponement of consumption among constrained applicants is about 36% (31%). The applicants are "positively selected", but not very different from the non-applicants.[20]

[19]These are simply the target group (178,000) multiplied by the fraction of constrained households (0.244) multiplied by the application rate among the constrained (0.679).We ignore consequences for non-constrained households with sufficient assets to smooth consumption. Given consumption, the gain from receiving a transfer today or in 10-12 weeks was negligible since the interest rate was close to zero.

[20]The average (median) P among constrained is 2289 (2059) NOK; constrained applicants 2374 (2166) NOK and constrained non-applicants 2112 (1830) NOK.

Table 3: **Robustness checks. Firm and family fixed effects.**

	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity constr (LC=1)	0.1868***			0.1719***		
	(0.004)			(0.049)		
Postponement (P/C)		0.3053***			0.2977***	
		(0.008)			(0.115)	
Excess Deposits (ED/C)		-0.0010***			-0.0006	
		(0.000)			(0.001)	
Postponement						
$[0.6, 1]$			0.2421***			0.2249**
			(0.007)			(0.096)
$[0.4, 0.6)$			0.2242***			0.1774**
			(0.007)			(0.090)
$[0.2, 0.4)$			0.2102***			0.2329***
			(0.006)			(0.077)
$(0, 0.2)$			0.1919***			0.1789**
			(0.005)			(0.071)
Excess Deposits						
$(1, 2)$			0.1705***			0.1268
			(0.011)			(0.140)
$[2, 4)$			0.1422***			0.1203
			(0.007)			(0.087)
$[4, 6)$			0.1213***			0.1172
			(0.006)			(0.083)
Family Dynasty Insurance						
ln(deposits parents + inlaws)	-0.0110***	-0.0108***	-0.0092***			
	(0.001)	(0.001)	(0.001)			
ln(deposits siblings)	-0.0115***	-0.0101***	-0.0099***			
	(0.001)	(0.001)	(0.001)			
Financial literacy						
Financial education	0.0146**	0.0170**	0.0141*	0.0052	0.0020	0.0104
	(0.007)	(0.007)	(0.007)	(0.094)	(0.093)	(0.095)
Constant	0.5257***	0.5658***	0.5969***	0.5174***	0.5498***	0.4511***
	(0.005)	(0.005)	(0.049)	(0.091)	(0.097)	(0.166)
Personal characteristics	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	Yes	No	No	Yes
Industry FE	No	No	No	No	No	Yes
Occupation FE	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes			
Family FE				Yes	Yes	Yes
Obs.	178537	178537	178537	178537	178537	178537
R^2	0.410	0.412	0.416	0.968	0.968	0.970

Notes: OLS estimates (std. err) of linear probability models. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Thus, many households had experienced a substantial temporary drop in consumption without the program.

The literature on the welfare costs of business cycles (following Lucas, 1987) provides a framework for quantifying it as the percentage increase in consumption that would be necessary to make a representative consumer indifferent between a smooth trend and a similar trend with transitory shocks. When these are random shocks around a trend growth path, the cost of business cycles is very small and often (much less) a percentage of consumption (Imrohoroğlu, 1989). Typically, these estimates are based on variation in consumption that is much smaller than what we observe here, and the welfare costs are derived from a lifetime perspective. We need a different approach and present estimates based on the simple framework in Section 4.

For each household, we simply calculate two alternative consumption flows, and the welfare gain is measured by the willingness to pay for smooth consumption (Z), defined by Equation (6):

$$Tln(C - Z) = Hln(C - P/H) + (T - H)ln(C + P/(T - H)) \tag{6}$$

Some straightforward calculations give an explicit solution for Z (since $Z < C$):

$$Z = C - (C - P/H)^h (C + P/(T - H))^{1-h}. \tag{7}$$

When h=H/T=0.5 (i.e. the delayed consumption is distributed over the same number of weeks as the handling time),

$$Z = C - (C^2 - (P/H)^2)^{0.5}. \tag{8}$$

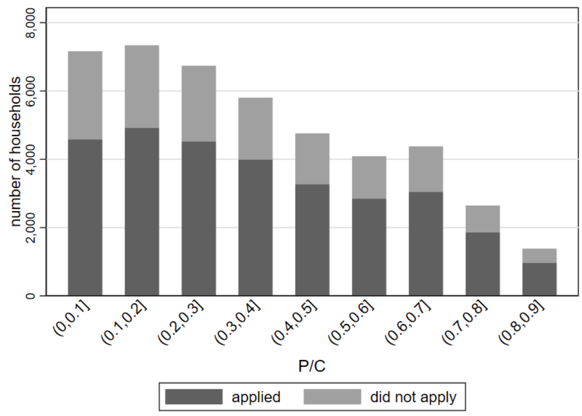
We can also scale the willingness to pay by consumption:

$$Z/C = 1 - (1 - (P/HC)^2)^{0.5}. \tag{9}$$

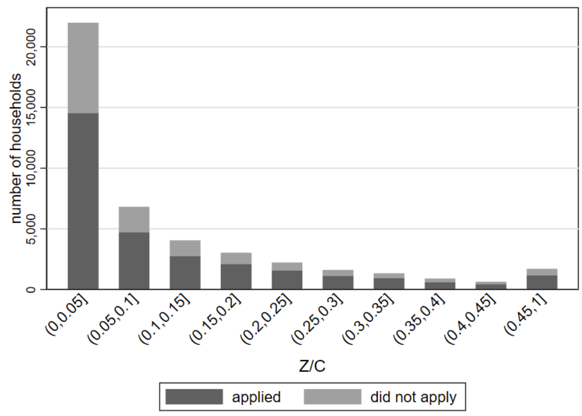
In this calculation, we assume that the household rationally allocates the available assets over the H weeks (in the absence of advance payments) with the same consumption each week. Recent US evidence (Ganong and Noel, 2019) suggests that some liquidity-constrained households are myopic or exhibit present-bias, based on the observation that consumption spending drops sharply at UI benefit exhaustion. Such a household could overspend early and experience even more volatile consumption.

The data allow us to estimate the willingness to pay for smooth consumption for each individual UI claimant. From Equation (9), we see that the estimated Z/C requires information on the weekly (smoothed) consumption level, as well as the postponement. The distribution of willingness to pay to avoid postponement is shown in Figure 4b. Among constrained applicants (dark bars), the average Z/C is 0.11 (11%). The distribution is skewed, as the median relative willingness to pay is just 5%. The last two panels in Figure 4 split the sample by partner status and clearly illustrate that the large program gains (in relative terms) are concentrated among single adult households. Among the constrained applicants, 59% are single and their average (median) willingness to pay is 16% (10%). The median willingness to pay for couple applicants is just 2%, substantially lower than the mean of 5%. When couples pool resources, they protect each other from income shocks.

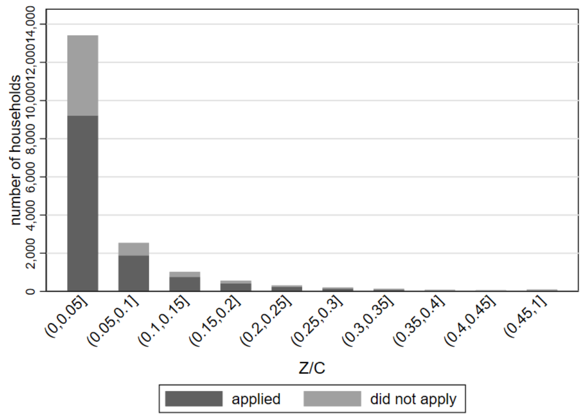
Figure 4: **Counterfactual postponed consumption and willingness to pay estimates, weekly.**



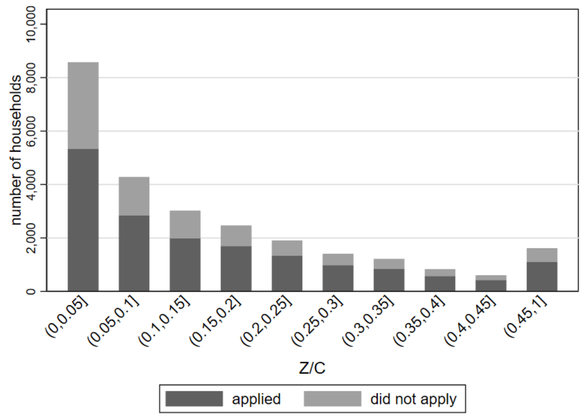
(a) Relative postponed consumption



(b) Relative willingness to pay



(c) Relative willingness to pay, couples



(d) Relative willingness to pay, singles

Notes: Panel (a) plots the distribution of postponed consumption relative to 'normal' consumption with no program for constrained households (P/C), split by application status. Panel (b) displays the distribution of willingness to pay to avoid consumption postponement (defined by Equation (8)) relative to 'normal' consumption (Z/C). Panels (c) and (d) contain the distribution of relative willingness to pay (Z/C) by family status — couples vs. singles, respectively. Consumption is estimated as max(seventy-five percent of weekly UI; ninety percent of household disposable income in 2019).

Table 4: **Weekly willingness to pay to avoid postponement.**

	Eligible (persons)	**Constrained (persons)**	**Applicant (persons)**	**Mean Z (NOK)**	**Total (1000 NOK)**
	(1)	(2)	(3)	(4)	(5)
All	178,537	44,267	30,013	496	14,891
Gender					
Male	95,705	27,450	18,810	548	10,312
Female	82,832	16,817	11,203	409	4,579
Family size					
Single no children	65,552	20,028	13,484	532	7,175
Single with children	28,633	6,658	4,459	411	1,834
Married no children	30,350	5,504	3,641	524	1,907
Married with children	34,214	6,252	4,358	407	1,775
Rest	19,788	5,825	4,071	541	2,200
Immigrant background					
Immigrant	47,851	17,029	11,426	560	6,398
Native	130,686	27,238	18,587	457	8,494
Education					
Less than high-school + N/A	52,714	18,876	13,198	513	6,770
High-school + Voc	74,937	17,417	11,615	494	5,737
Bachelors	38,323	6,296	4,130	467	1,930
Masters and PhD	12,563	1,678	1,070	425	455

Notes: Column (4) is the average willingness to pay to avoid postponement (Z) when the relative willingness to pay (Z/C) is winsorized at 20 percent, in NOK. Column (5) is the total willingness to pay calculated as the sum of 'adjusted Z' across constrained applicants, in 1000 NOK. As a robustness check, Table A.3 repeat the exercise using an individual random draw of H between 3 and 16, with probabilities from the observed distribution of H by type of unemployment.

In Table 4, we report the total estimated willingness to pay in the first row and also by groups to illustrate the distributional consequences of the program.[21] Our estimate of 15 million NOK per week for 20 weeks can be compared to a total program transfer of about 3000 million NOK in the first 8 weeks. The program gains are greatest for men, singles, less educated, and immigrants. These estimates are based on a common handling time of 10 weeks for all. As a robustness check, we calculate the gains using an individual random draw of H between 3 and 16, with probabilities from the observed distribution of H, and the results are very similar (Table A.3).

The estimated median program gain of 5% of consumption is not easily compared to existing studies of welfare effects of UI institutions. We are not aware of any study that estimates the welfare loss of delayed benefits. Studies of UI generosity and consumption suggest that a 10 percentage point increase in the replacement rate reduces the drop in

[21] We find it unlikely that households are willing to give up more than 20% of their consumption to avoid the postponement and interpret the upper tail of the Z/C distribution as a measurement error. Therefore, we winzorize Z/C at 0.2 before multiplying with C to get the numbers reported.

consumption during unemployment in the range of 1% to 6%.[22] Thus, to raise consumption by 5% with a higher replacement rate, it requires a substantial increase — from 8.3 (10*5/6) to 50 (10*5/1) percentage points. The entitlement period is an important element of the UI system and recent US evidence (Ganong and Noel, 2019) suggests that gains from the extension of UI benefits are four times larger than spending the same tax revenue on increased per day benefits. The program gain is then comparable to the transfers needed to increase the replacement rate by 2-12.5 percentage points (10*5/6*4 or 10*5/1*4), but spent on extending the maximal UI period. We would like to stress that one needs to approach these comparisons with caution, recognizing the nuanced differences in the environmental and contextual settings complicates direct comparisons and interpretations. In particular, the maximum UI duration is much longer in Norway than in the US.

While the welfare gains from the program arise from improved consumption smoothing, the costs are both fixed and variable depending on the number of applicants (Table 5). The main fixed costs are labor input to the construction of the Web portal for the application process, coding eligibility checks, and payment mechanisms. Since the program operated after less than a week, the fixed costs here are limited to less than a week of hours for the programmers and designers involved. The eligibility checks[23] and payments were automatic with no manual discretion. Because the program was set up building on preexisting infrastructure, the marginal transaction costs per application were close to zero. However, during the first week of the program it was revealed that not all applicants had an account number to receive the money.[24] A text message was sent to UI applicants asking them to check the account number and remind them of the possibility of an advance payment.[25] Associated costs were approximately 35 øre (approximately 4

[22]For example, Gruber (1997) reports a 2.8% decline, Browning and Crossley (2001) report 0.8%, while East and Kuka (2015) report a range from 1% on average and 6% during periods of high national unemployment.

[23]It is important to note that in 'normal' times, the determination of eligibility for the UI payments involves a comprehensive assessment based on numerous criteria and not all criteria carry equal weight in the evaluation process. In the interest of timely and automated processing to facilitate prompt disbursement of payments, deliberate trade-offs have been made.

[24]According to an internal NAV memo, out of 230,000 applicants in week 13, 6300 (2.7%) did not have or had invalid account number.

[25]The following text was used "Sjekk om du har registrert riktig kontonummer

cents) per message and some fixed costs for arrangements with the mobile operator — *Telia*. In total around 350,000 SMS text messages were sent out in two rounds (230,000 + 118,000), amounting to less than 150,000 NOK in communication costs.

Table 5: **Program costs.**

Category	Task	Type of costs	Estimate
(1)	(2)	(3)	(4)
Infrastructure	Development, algorithms, integration of the in-advance payment into existing infrastructure	Personnel: Ten full-time employees for one week	Small (0.3 mln NOK)
Communication	Website, text messages, information	PR, SMS-text	Small (<0.2 mln NOK)
Payment	Money transfers, monitoring	Existing infrastructures, low marginal costs	Negligible
Repayment	Repayment management	Personnel: Estimate based on no. of cases	Substantial (< 116 mln NOK)

Notes: Our estimates are based on input and conversations from representatives of NAV; Trond Jørgensen, Audun F. Strand and Peter C. Vold. Cost of one day of work is 5460 NOK, including wages and social costs (e.g. payroll taxes, mandatory employer insurance and holiday pay), IT equipment and office costs (adapted from Løyland et al., 2023).

After all, the automated individual input in the benefit formula was not perfectly measured without error, and subsequent manual handling of the UI claim often revealed that the algorithm did not correctly define eligibility. The advance program algorithm estimated eligibility from administrative earnings records, but a substantial number of their ordinary UI application were rejected as they failed on other criteria. In practice, some thousand applicants received excess advance payments. The administration first deducted the entire excess advance from the first payment of the ordinary UI benefit. However, after media coverage of this "unfair treatment", NAV allowed advance payment recipients to choose a longer repayment period of up to 36 months. As a consequence, substantial administrative resources were needed to handle the repayment of advance benefits. Based on the information provided by the NAV representatives, the financial unit had on average 400 cases/inquiries per month until September 2023. These inquiries included various tasks, such as invoice/postponement inquiries, balance assessments, and

https://www.nav.no/kontonummer. Du kan nåogsåsøke om forskuddsutbetaling. Hilsen NAV".

other manual processes. Using insights from Løyland et al. (2023), which establishes a unit cost of 1625 NOK for handling audits by Tax administrators in 2014, with an estimated rate of 3 cases per day, we assume that the unit cost for overseeing repayments within NAV is comparable. Extrapolating this cost metric and adjusting for inflation, we calculate the cost of one day of work as 5460 NOK and estimate the total cost of the repayment scheme. By September 2023, 38,500 cases were left. Since the remaining cases are expected to be more complex, we double the estimated (average) hours of work. Given these numbers, the total expenses of the repayment scheme are projected to be less than 116 million NOK.[26]

Calculated program gains and costs come with some important caveats. Most importantly, they are ex post and based on how the crisis actually turned out. The program was constructed under high uncertainty. Ideally, an evaluation of welfare gains should be ex-ante, weighting alternative magnitudes of the unemployment shocks, handling time, and consumption postponement in the absence of an in-advance program. Generally, since the labor market consequences turned out less dramatic than expected in early April 2020, an ex-post evaluation underestimates ex-ante gains. Our estimate that one in four households would have been liquidity-constrained is probably an upper bound. This leads to an overestimation of the program gains, but dilutes the difference in application behavior between constrained and non-constrained households. A substantial number of households had access to credit from their family network or financial institutions. Although we observed the financial capacity of family networks, without transaction data, we cannot tell how this would have been realized for actual access to credit. Information on household credit ratings is not available for the whole sample. Households could have access to credit cards, but US evidence suggests that (surprisingly) few draw on those during periods of unemployment (Ganong and Noel, 2019).

[26] Up to September 2023, 400 cases per month for 20 months with each case taking about 1.5 hours of work (upper bound) resulting in 2,000 full working days. The total cost is then around 11 mln NOK (2000×5460). From September 2023 onward, we estimate 3 hours of work per case (half of full day) with 38,500 cases equaling 105 mln NOK ($38500 \times 5460/2$) in total costs.

8 Conclusion

During the initial phase of the COVID-19 pandemic, the Norwegian administration anticipated long delays in processing the massive number of UI claims. This study examines the effectiveness of the in-advance payment program that was introduced to alleviate the consequences for liquidity-constrained families. Our findings reveal that approximately half of the eligible UI claimants requested advance payments. The probability of application varied based on various household characteristics, including educational attainment, immigration status, and family size. We estimate that one in four eligible UI claimants lived in liquidity constrained households, defined as those with bank deposits less than ten weeks of the post-tax UI benefits. UI claimants in constrained households were 20 percentage points more likely to apply for the in-advance payments compared to the non-constrained. In addition, the analysis explored the impact of access to family credit on application rates. Our evidence suggests that having parents with higher bank deposits decreases the application rate for households with limited own assets, indicating the importance of family support in mitigating liquidity constraints.

The primary beneficiaries of the program are approximately 30,000 households that, in the absence of access to advance payments, would have had to postpone their consumption on average by 36% while waiting for their UI claim to be processed. To quantify the welfare gains of the program, we impute two consumption flows, with and without advance payments. Using a simple log-linear utility function model, we then estimate the willingness to pay for smooth consumption for each household. Among constrained applicants, the average and median willingness to pay is 11% and 5% of their consumption, respectively. Notably, the largest (relative) program gains in terms of willingness to pay are concentrated among single households — 16% on average. Couples, assumed to pool resources, tend to have a lower willingness to pay — 5%.

Program implementation costs were low due to the existing administrative register infrastructure that automatically assesses eligibility. However, overpayment caused by imperfect algorithms led to program-implied costs for managing a repayment scheme. However, our estimated gain from improved consumption smoothing among (otherwise) constrained families exceeds the program costs by a wide margin.

The analysis extends beyond the immediate program takeup, shedding light on broader implications of welfare programs. Specifically, our study enriches the discussion on liquidity constraints and their impact on consumption patterns, offering nuanced insights into the complexities of household financial vulnerability. In particular, our findings emphasize that even a modest adjustment, such as timely support, can substantially alleviate disruptions in consumption for those in need. These results are informative for future policy decisions, especially in the design and implementation of programs aimed at mitigating the impact of temporary external shocks on household income.

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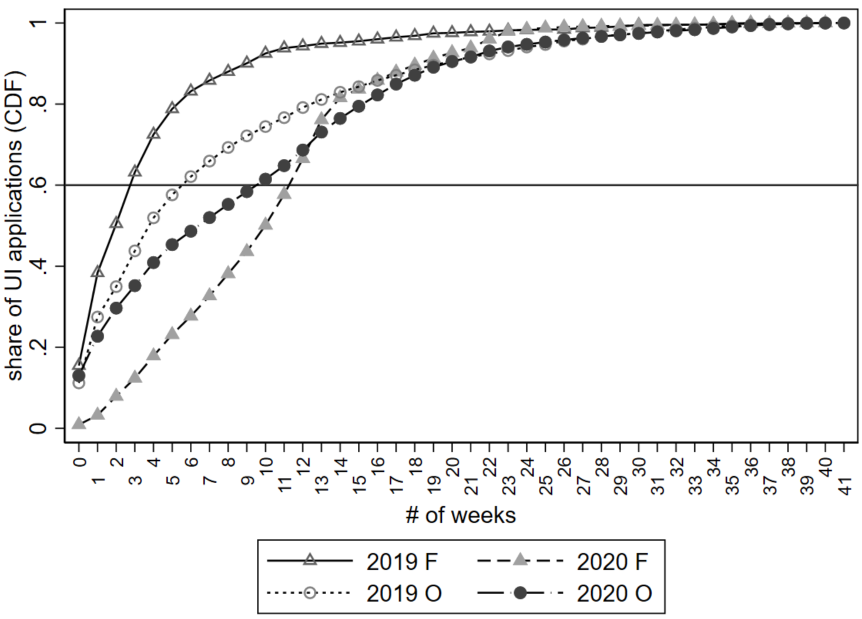
Appendix

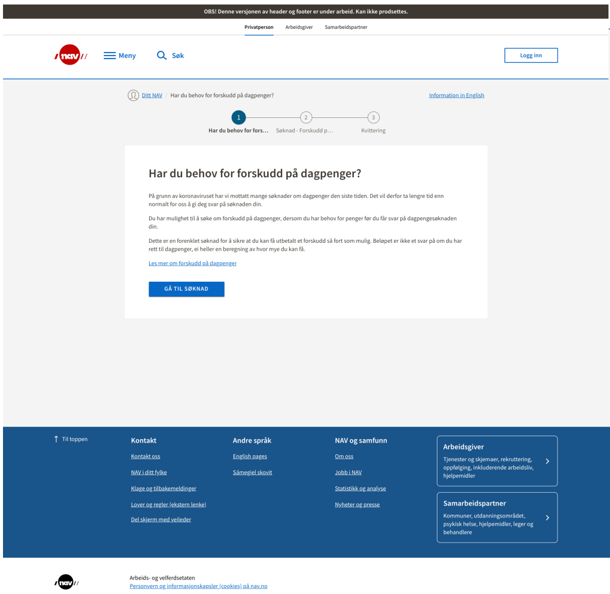
A Additional Figures and Tables

Figure A.1: **Handling time by UI eligibility.**

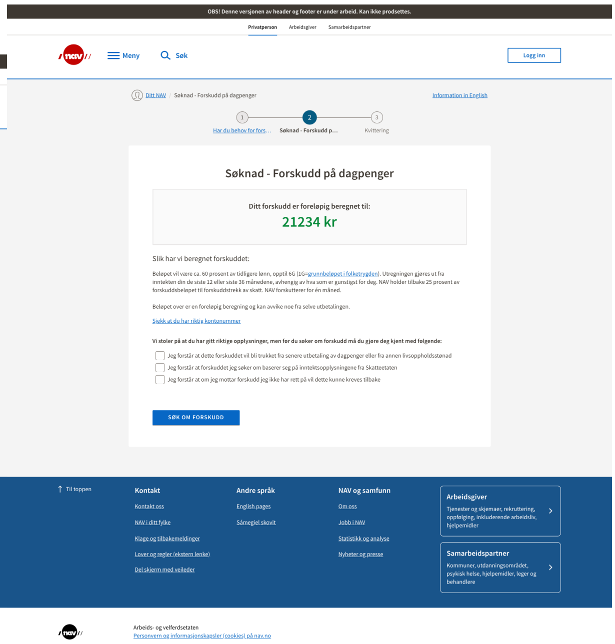


Notes: F - on furlough; O - ordinary unemployed.

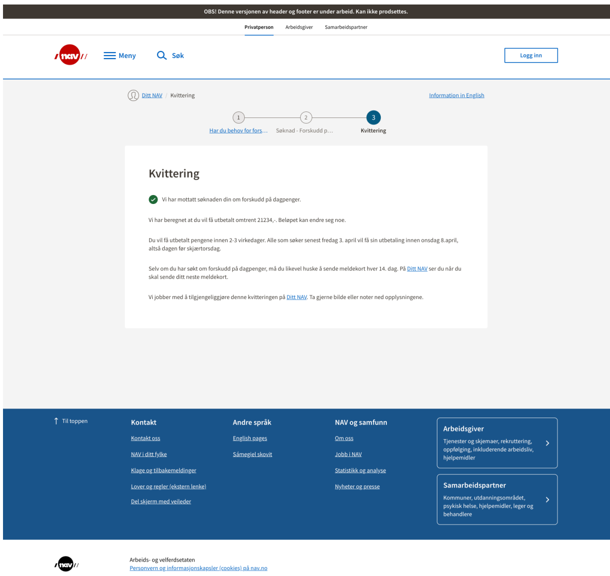
Figure A.2: **Screenshots. Filing Application.**



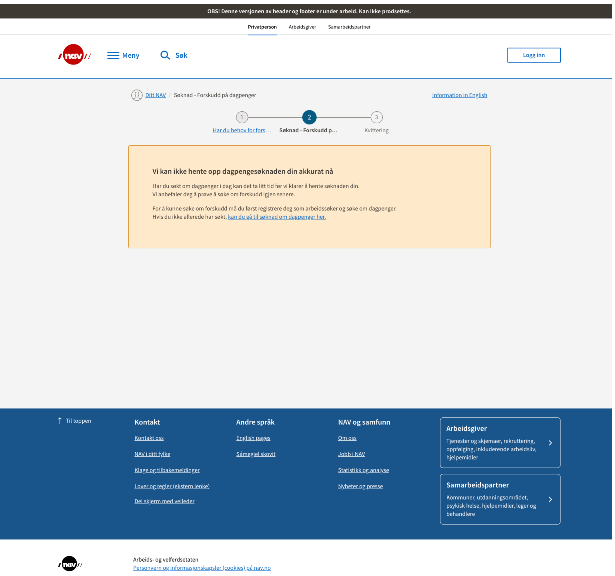
(a) Initial Online Application



(b) Advance Calculation



(c) Application Receipt



(d) Application Error

Notes: Panel (a): 'Do you need an advance on unemployment benefits?' with a prominent 'Go to Application' button, highlighting the first step in the application process. Panel (b): The application displays a preliminary advance on unemployment benefits, providing transparency on the calculation process. Users are required to acknowledge key points, including deductibility from subsequent benefits, reliance on salary information from Tax Administration, and the possibility of reclaiming the amount if eligibility criteria are not met. Panel (c): Confirmation of application submission and the advance amount. Details include the acknowledged receipt, the calculated advance from the previous step, and information about the expected disbursement timeframe. Users are reminded of their ongoing reporting obligations, with efforts underway to provide the receipt on Ditt NAV for future reference. Panel (d): The application for an in-advance UI payments involves a two-step process: registering as a job-seeker and applying for UI. Upon application for in-advance, individuals may encounter a notification stating that their UI claim is not processed, advising them to try the in-advance application later.

Figure A.3: **Internal Memo.**

// NOTAT

Til: Jane Hellstrand

Kopi til:

Vår referanse: 20/7824
Fra: Seksjon for økonomi- og styringssystem
Saksbehandler Hilde Gunnufsen
Dato: 12.04.2020

SMS til brukere for kontroll av kontonummer

Det har i forbindelse med koronaepidemien kommet om lag 300 000 søknader om dagpenger til NAV. Når vi nå skal kjøre så mange utbetalinger er det viktig å redusere belastningen på NAV samtidig som vi må sikre at bruker får pengene på konto så raskt som mulig.

ØS bestilte i uke 13 en kontroll av 230 000 brukere som har søkt om dagpenger fra NAV mot TPS for å sjekke at de har kontonummer. Av disse er det 6300 brukere som ikke har kontonummer.

Utbetaling uten kontonummer generer et utbetalingskort. Det er en ulempe for både bruker og NAV

- Bruker får utbetalingen senere, da det tar tid å generere utbetalingskort og det må sendes pr post. Det er en forutsetning at bruker er på den adressen som ligger i folkeregisteret eller midlertidig adresse som er meldt til NAV.
- Bruker må heve utbetalingskortet i bank og det påløper som oftest gebyr
- Kostnadene for NAV er vesentlig høyere når det genereres utbetalingskort (bankkostnader)
- Utbetalingskort som ikke blir hevet må følges opp av NAV hvilket er tidkrevende og det koster penger (bankkostnader)

Det antas at flere brukere som er registrert med kontonummer ikke har et gyldig kontonummer, noe som avdekkes i det transaksjonene behandles i banken.

Retur av en utbetaling er en ulempe for både NAV og bruker

- Bruker får ikke pengene til forventet tid
- NAV får utbetalingen i retur og det går en melding til NAV kontoret om at de må fremskaffe kontonummer til bruker
- NAV må kontakte bruker pr post, telefon eller modia og bruker må registrere kontonummer. I flere tilfeller kan det være vanskelig å finne eller få tak i bruker.
- NAV kontoret må sende melding til NØS om at ny utbetaling kan genereres hvis bruker har registrert kontonummeret i selvbetjeningsløsningen. Alternativt må NØS først registrere kontonummer for så å utbetale ytelsen.

NAV har siste uken forbedre informasjonen vesentlig. Det ligger nå inne flere varsler i søknadsprosessen og som info på nav.no om at bruker må registrere korrekt kontonummer. De første ca 230 000 søkerne hadde ikke denne informasjonen.

Beslutning
Den 30.3.2020 har ØS i samråd med KOM besluttet at det sendes ut SMS til brukere som har søkt dagpenger etter utbrudda av korona der vi ber de kontrollere at de har korrekt kontonummer.
Det sendes ut til de første 230 000 brukere – de som søkte om dagpenger før det ble lagt ut informasjon om registrering av kontonummer. Vi starter med å sende til de som ikke har kontonummer. Deretter har vi sortert på dato kontonummeret ble registrert i TPS.

Mobilnummer hentes fra KRR.
Vi sender ikke til brukere som er reservert i KRR – 1982 stk

Vi bruker SMS tjenesten til Telia. Koster ca 35 øre pr melding under 181 tegn. I tillegg påløper noen kostnader for å tilrettelegge fra Telia. NAV vil stå som avsender.
Altinn ble vurdert som avsender, men de trengte ca 1 uke for å tilpasse meldingen med NAV som avsender (og ikke ALTINN)

SMSen har følgende tekst:

> Sjekk om du har registrert riktig kontonummer https://www.nav.no/kontonummer
> Du kan nå også søke om forskuddsutbetaling
> Hilsen NAV

Den 2.4.2020 ba KOM at det også sendes SMS til brukere som har søkt om dagpenger i perioden 23.4 til 2.4. Det ble 3. april sendt ut ca 118 000 SMS. Meldingen var den samme og utsendelsen ble gjort puljevis i puljer av 20 000 brukere.

For mer detaljer se Jira-sak 104098

Fagsystemer / FAGSYSTEM-104098
SMS varsling søknad om utbetaling

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Notes: SMS Notification for Account Verification. The memo discusses the implementation of an SMS campaign by NAV, targeting individuals who applied for unemployment benefits. It emphasizes the verification of account numbers and the option to apply for an advance payment, outlines the prioritization of message recipients, and provides details on the associated costs.

Table A.1: **In advance application probability, complete.**

	(1)	(2)	(3)	(4)	(5)	(6)
ln(Deposits)	-0.0604***					
	(0.001)					
ln(UI Benefits)	0.0883***					
	(0.003)					
Liquidity constr (LC=1)		0.1975***		0.1462***	0.1445***	
		(0.003)		(0.004)	(0.004)	
Postponement			0.3180***	0.0762***	0.0765***	
			(0.007)	(0.009)	(0.009)	
Excess Deposits			-0.0010***	-0.0009***	-0.0009***	
			(0.000)	(0.000)	(0.000)	
Postponement						
$[0.6, 1]$						0.2470***
						(0.005)
$[0.4, 0.6)$						0.2317***
						(0.005)
$[0.2, 0.4)$						0.2214***
						(0.004)
$(0, 0.2)$						0.2025***
						(0.004)
Excess Deposits						
$(1, 2)$						0.1672***
						(0.008)
$[2, 4)$						0.1469***
						(0.005)
$[4, 6)$						0.1302***
						(0.005)
Family Dynasty Insurance						
ln(deposits parents + inlaws)		-0.0118***	-0.0119***	-0.0101***	-0.0101***	-0.0097***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(deposits siblings)		-0.0138***	-0.0124***	-0.0116***	-0.0109***	-0.0114***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
missing parent = 1		-0.0256***	-0.0203***	-0.0225***	-0.0177***	-0.0207***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
missing sibling = 1		-0.0087**	-0.0076**	-0.0080**	-0.0071*	-0.0079**
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Financial literacy						
Financial education	0.0140**	0.0177***	0.0196***	0.0194***	0.0111*	0.0101*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
N/A	-0.0453***	-0.0219	-0.0326**	-0.0278*	-0.0263*	-0.0190
	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)
UI eligibility						
unemployed	-0.1933***	-0.1935***	-0.1908***	-0.1921***	-0.1624***	-0.1640***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education						
high-school	-0.0364***	-0.0363***	-0.0383***	-0.0358***	-0.0336***	-0.0309***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
voc	-0.0226***	-0.0227***	-0.0256***	-0.0221***	-0.0125*	-0.0100
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
bachelor	-0.0429***	-0.0482***	-0.0501***	-0.0452***	-0.0451***	-0.0423***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
MA+PhD	-0.0724***	-0.0837***	-0.0839***	-0.0773***	-0.0710***	-0.0687***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N/A	-0.0192*	-0.0237**	-0.0207*	-0.0223*	-0.0224*	-0.0234**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
Gender						
female	-0.0014	-0.0143***	-0.0133***	-0.0125***	-0.0199***	-0.0221***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Marital status						
married	0.0127***	0.0124***	0.0091***	0.0082**	0.0054*	0.0049
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
widowed	0.0047	-0.0007	0.0164	0.0151	0.0182	0.0017
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
divorced	0.0669***	0.0763***	0.0749***	0.0715***	0.0673***	0.0662***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N/A	-0.0517***	-0.0370***	-0.0460***	-0.0438***	-0.0487***	-0.0454***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Immigration status						
immigrant	0.0084***	0.0355***	0.0322***	0.0314***	0.0285***	0.0319***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of family members						
2	0.0120***	-0.0061*	-0.0038	-0.0036	-0.0048	-0.0057*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
3	-0.0242***	-0.0398***	-0.0379***	-0.0375***	-0.0345***	-0.0371***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
4	-0.0532***	-0.0692***	-0.0693***	-0.0675***	-0.0618***	-0.0633***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
5+	-0.0754***	-0.0939***	-0.0918***	-0.0910***	-0.0824***	-0.0849***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Number of children						
1	0.0485***	0.0508***	0.0488***	0.0468***	0.0442***	0.0460***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
2	0.0738***	0.0744***	0.0742***	0.0708***	0.0634***	0.0645***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
3+	0.1131***	0.1190***	0.1190***	0.1136***	0.1057***	0.1056***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age group						
30-39	-0.0000	0.0145***	0.0172***	0.0149***	0.0139***	0.0073**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
40-49	-0.0124***	0.0056	0.0097**	0.0078**	0.0060	-0.0055
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
above 49	-0.0625***	-0.0516***	-0.0396***	-0.0395***	-0.0428***	-0.0627***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.5721***	0.5335***	0.5754***	0.5578***	0.4629***	0.4172***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.008)
Occupation FE	No	No	No	No	Yes	Yes
County FE	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes
Obs.	178537	178537	178537	178537	178537	178537
R^2	0.085	0.068	0.070	0.076	0.093	0.094

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: **Robustness checks: Selected sample.**

	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity constr (LC=1)	0.1986***			0.2199***		
	(0.003)			(0.010)		
Postponement		0.3192***			0.3607***	
		(0.007)			(0.027)	
Excess Deposits		-0.0011***			-0.0009***	
		(0.000)			(0.000)	
Postponement						
$[0.6, 1]$			0.2524***			0.2560***
			(0.006)			(0.019)
$[0.4, 0.6)$			0.2322***			0.2208***
			(0.006)			(0.019)
$[0.2, 0.4)$			0.2201***			0.2589***
			(0.005)			(0.015)
$(0, 0.2)$			0.2040***			0.2274***
			(0.005)			(0.014)
Excess Deposits						
$(1, 2)$			0.1721***			0.1488***
			(0.009)			(0.029)
$[2, 4)$			0.1461***			0.1515***
			(0.006)			(0.019)
$[4, 6)$			0.1304***			0.1188***
			(0.005)			(0.017)
Family Dynasty Insurance						
ln(deposits parents + inlaws)	-0.0114***	-0.0114***	-0.0094***			
	(0.001)	(0.001)	(0.001)			
ln(deposits siblings)	-0.0139***	-0.0122***	-0.0113***			
	(0.001)	(0.001)	(0.001)			
Financial literacy						
Financial education	0.0216***	0.0231***	0.0125**	0.0150	0.0147	0.0229
	(0.006)	(0.006)	(0.006)	(0.020)	(0.020)	(0.020)
Constant	0.5283***	0.5722***	0.5143***	0.5704***	0.6143***	0.4742***
	(0.004)	(0.005)	(0.045)	(0.014)	(0.016)	(0.030)
Personal characteristics	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	Yes	No	No	Yes
Industry FE	No	No	Yes	No	No	Yes
Occupation FE	No	No	Yes	No	No	Yes
Obs.	147887	147887	147887	14161	14161	14161
R^2	0.064	0.067	0.090	0.072	0.071	0.107

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS estimates (std. err) of linear probability models. Robust standard errors in parentheses. In columns (1)-(3), the sample is restricted to groups of UI recipients from the same firm (colleagues sample). In columns (4)-(6), the sample is restricted to groups of UI recipients from the same family (siblings pairs sample). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: **Weekly willingness to pay to avoid postponement.**

	Eligible (people)	Constrained (people)	Applicant (people)	Mean Z (NOK)	Total (1000 NOK)
	(1)	(2)	(3)	(4)	(5)
All	178,537	41,344	28,137	499	14,030
Gender					
Male	95,705	25,685	17,630	550	9,702
Female	82,832	15,659	10,507	412	4,328
Family size					
Single no children	65,552	18,817	12,700	535	6,790
Single with children	28,633	6,193	4,179	413	1,724
Married no children	30,350	5,128	3,412	525	1,791
Married with children	34,214	5,723	3,999	410	1,638
Rest	19,788	5,483	3,847	543	2,087
Immigrant background					
Immigrant	47,851	15,947	10,751	564	6,060
Native	130,686	25,397	17,386	458	7,970
Education					
Less than high-school + N/A	52,714	17,729	12,432	514	6,392
High-school + Voc	74,937	16,181	10,824	500	5,412
Bachelors	38,323	5,868	3,887	463	1,799
Masters and PhD	12,563	1,566	994	430	427

Notes: For random H between 3 and 16, with probabilities from the observed distribution of H by type of unemployment. Column (4) is the average willingness to pay to avoid postponement (Z) when the relative willingness to pay (Z/C) is winsorized at 20 percent, in NOK. Column (5) is the total willingness to pay calculated as the sum of 'adjusted Z' across constrained applicants, in 1000 NOK.

B Data construction.

B.1 Sample

To construct the sample for the analysis, we combine the information from 4 sources: employment status from 'labor report cards' data; 'decision on UI' data; 'advance pay program UI' data; and, 'UI payments' data. The main data is 'UI payments' (NAV UTB dagpenger), that captures information on unemployment insurance recipients from January 1, 2018 to March 13, 2022. However, first, we want to limit our analysis on individuals that entry the unemployment sometime between March and May of 2020 (weeks 11 and 22), which corresponds to the start of the advance pay program. All steps of the construction of the sample are summarized in Table B.4. By limiting our attention to entrants by the end of May, we capture almost 90% of all advance pay program recipients (Steps 1a-2a).

We start the sampling of individuals using the 'labor report cards'. These are a collection of weekly reports by individuals on their (un)employment status. Using this reports, we sample individuals that 'newly' entered the unemployment sometimes between March and May 2020. By 'newly' unemployed we mean either individuals that have never reported as being unemployed before, as well as those that have some history of unemployment but was employed (i.e. did not report the status) at least 4 weeks prior to COVID-19 (Steps 1b-8b).

Employment status data allows us to identify the start of the unemployment period more precisely. However, reports on the status does not necessarily guarantee that the individual is eligible for the UI. To this end, using information in 'decision data', we identify those who are eligible for the UI, and *decision date* reports when the application was actually processed. Hence, comparing it with the first employment status reporting week roughly gives us the application processing time (Steps 1c-6c). Merged employment status and decision samples, constitute the population sample for the analysis - individuals that entered the unemployment during March-May 2020 and were eligible for unemployment insurance (Step A).

Our core data source - unemployment insurance payments - reports the UI recipients with the period and the amount received. For some individuals apart from usual UI payments, some 'additional' payments are reported separately, and we keep only the UI benefits. By merging it with the 'employment status - decision' sample from step A, we make sure to have the sample of 'newly' unemployed. Moreover, the data differentiates between 4 different unemployment types: (i) unemployment benefit for fishing industry; (ii) unemployment benefits during layoffs, i.e. furlough; (iii) wage guarantee funds - unemployment benefit; and, (iv) ordinary unemployment benefit, i.e. unemployed. For the analysis, we keep furlough and unemployed (Steps 1d-4d). Lastly, we merge our sample of interest with the 'advance pay program UI' sample, to identify individuals that applied for the program (Step B).

Finally, the unique individual identifier used in Norway across different databases allows us to complement the UI data with the data on individual financial data and different demographic characteristics (Steps C and D). More details on these are described in the next subsection.

B.2 Variables

Education

Originally, the level of education of the individual is based on The Norwegian Standard Classification of Education (NUS2000). The system is used for grouping people's education activities and educational background on a 6-digit level. We simplify it to 6 categories: 1 - below high school educational attainment; 2 - high-school graduate; 3 - vocational education; 4 - bachelor's degree; 5 - Master's and Ph.D. degrees; 6 - information on education level is not available. We use the reports for the 2019 year.

The first group includes the NUS codes that start with 0 -no education and preschool education, 1-primary education, 2-lower secondary education, 3-upper secondary education, basic education, and 9-unspecified. The second group is for NUS code 4-upper secondary, final year; the third group is reserved for NUS code 5-post-secondary non-tertiary education. The fourth group covers the NUS code 6-first stage of tertiary education, undergraduate level, while the fifth group combines the NUS codes 7-first stage of tertiary education, graduate level, and 8-second stage of tertiary education (postgraduate education). The last group is reserved for individuals for which information on education attainment is unavailable.

Financial literacy

Similar to Christiansen et al. (2008) and Guiso and Jappelli (2005), we define financial literacy as completing Economics (or related) program at tertiary education levels or having short-cycle higher education in economics.

By this definition, we identify the following NUS codes:

- 5/6/7/8 34 - Economics (the first digit is for high school/BA/MA/Ph.D. levels, respectively);
- 5/6/7/8 4 - Business and administration;

Table B.4: **Data cleaning steps.**

	Step	# of ID	% of total	# of observations
Raw data: 'advance pay program'		196,795	100	641,455
1a	Drop obs for January	196,794	100	641,453
2a	Applications in March 1-May 31	175,161	89	376,795
Raw data: 'employment status'		945,949	100	24,990,969
1b	Keep if employment status < 3	933,130	98.64	22,255,497
2b	drop if unemployment ends before COVID (w11)	729,548	77.12	19,117,943
3b	drop duplicates	729,547	77.12	19,117,874
4b	People with 'gaps' in their unemployment. Set the cutoff gap for 1 month (4 weeks) before COVID. Ignore all obs. before the gap.	729,547	77.12	16,034,038
5b	The end week is set to the week before the 1 month gap that occurs after May 31, 2020 - week 22 of 2020. Ignore all obs. after the gap.	729,547	77.12	13,809,998
6b	Keep only "new" entrants as of 2020w11	641,917	67.86	9,128,543
7b	Focus entry period: March-May, 2020 (w11 - w22)	423,985	44.82	2,299,771
8b	Collapse by ID	423,985	44.82	423,985
Raw data: 'decision on UI'		384,637	100	6,367,452
1c	keep if vedtakfaktatypenavn == "UKESATS"	384,637	100	1,150,750
2c	keep if saktypenavn == "Ny rettighet" (ignore endring and gjenopptak)	371,401	96.45	439,037
3c	Drop duplicates	371,401	96.56	438,538
4c	Drop obs before March 12, 2020	300,771	78.20	342,759
5c	Keep obs for 2020	251,647	65.42	266,393
6c	Collapse by ID	251,647	65.42	251,647
A	merge 'employment status' and 'decision on UI'	203,232		203,232
Raw data: 'UI payments'		545,654	100	9,296,299
1d	keep only UI payments	545,075	99.9	8,769,196
2d	keep individuals from the 'employment status - decision' sample	189,127	34.67	2,309,169
3d	keep ordinary unemployed and furlough	187,674	34.39	2,288,706
4d	collapse by ID	187,674	34.39	187,674
B	merge with data on 'advance pay' applicants	187,674	34.39	187,674
C	merge with data on deposits and keep non-zero deposits	178,537	32.72	178,537
D	merge with demographics data	178,537	32.72	178,537

- 5/6/7/8 53 - Mathematics and statistics;
- 659904 - College degree, computer science, and economics, 2yrs;
- 659905 - College degree, IT and economics, 2yrs;
- 659907 - College degree, technical and business program, 3yrs;
- 759909 - Graduate engineering degree, industrial economics, and tech.management;
- 759915 - MA, technology, industrial economics, and tech.management, 5yrs;
- 759916 - MA, technology, industrial economics, and tech.management, 2yrs;
- 859909 - Ph.D., industrial economics and tech. management.

Generate financial education variable equal to 1, if the individual or the spouse/partner completed one of the above degrees in the last 5 years, i.e. 2015-2019, and 0 otherwise. Collect all individuals with no information on education in a separate group.

Marital status

Original 9 categories of marital status are collected to form 4 groups, plus one for missing information (the original code is specified in the brackets):

1. single (1);
2. married (2) and registered partner (6);
3. widowed (3) and widowed partner (9);
4. divorced (4), separated (5), separated partner (7), and divorced partner (8);
5. information is not available.

We use the marital status reported for 2019.

General characteristics

Gender

1. Male;

2. Female.

Immigration status

Originally 6 categories:

- A - without immigration background;

- B - first-generation immigrant, without a Norwegian background;

- C - born in Norway by two foreign-born (descendants);

- E - foreign born with a Norwegian parent;

- F - Norwegian-born with a foreign-born parent;

- G - born abroad with two Norwegian parents (includes foreign adoptees).

For the analysis, we combine the 6 distinct categories to identify immigrants (B) and natives (A/C/E/F/G).

Age

Identify the age of an individual for 2019 as $age = 2019 -$ the year of birth. The sample population age is between 15 and 66. Arrange individuals into 4 age groups:

1. below 30 y.o.;

2. between 30 and 39 y.o.;

3. between 40 and 49 y.o.;

4. above 49 y.o.

Family ties

For each individual in the sample, we observe parents' IDs and based on mother-ID we identify individuals' siblings (for individuals with missing mother-ID, we identify siblings based on the father's ID, where applicable). Individuals with missing information on both parents' ID are most likely to be of immigrant background.

Number of people in the family

Create 5 groups based on the family size: 1, 2, 3, 4, and at least 5.

Number of children aged 0-17

Create 4 groups by the number of under-age children: None, 1, 2, and at least 3.

Household identifier

Match each individual's ID in the sample with the ID of the spouse/partner. Generate household identifiers for couples. Individuals with no information on their spouse or partner are treated as a single-member household.

Bank deposits

We use the information on bank deposits (the amount by the end of 2019) as liquid assets to cover up for the lost income. The bank deposits are calculated at the household level meaning that we sum own bank deposits and the spouse/partner deposits - household deposits. For single-member households, the household deposit is equivalent to own deposits.

Family dynasty insurance

As family insurance proxy, we utilize the parents' (and siblings) bank deposits. To this end, for each individual in the sample, we sum deposits for that individual's parents' deposits and parents-in-law's deposits. For siblings deposits, we sum the deposits of children of the parent excluding the individual's own deposit.