Early pension withdrawal as stimulus*

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Abstract

During the COVID-19 pandemic, the Australian Government allowed the withdrawal of up to A$20,000 (around half median annual wage income) from private retirement accounts, ordinarily inaccessible until retirement. One in six withdrew A$38 billion (2% of GDP). These transfers were much larger than those typically considered in the literature and represented a liquidity shock, holding lifetime income constant. Using administrative and high-frequency bank transactions data, we find a high marginal propensity to spend given the size of the transfers of at least 0.43–0.48 within eight weeks. Gambling was the largest discernible spending category (larger than credit card repayments). Low levels of saving and savings and high levels of gambling prior to withdrawal strongly predict withdrawal and spending. We develop and calibrate a heterogeneous agent model, which fails to match the data with liquidity constraints or impatience alone; only under present bias ($\rho = 0.58$) can the model replicate the observed spending response.

JEL codes: E21, E63, E71, H31, H55, J32
Keywords: Stimulus, pension, liquidity, marginal propensity to consume, heterogeneous agent model, present bias

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1 Introduction

There is a long literature documenting much larger responses to cash transfers than would be predicted under the permanent-income hypothesis (PIH) and Ricardian equivalence (Ricardo, 1820; Friedman, 1957; Barro, 1974).[1] Cash transfers constitute a tiny fraction of lifetime income, so a rational, forward-looking, and liquid person would increase consumption only by a tiny fraction in response—or not at all given higher future taxes. Scholars have proposed two broad explanations for these responses: 'behavioral', considering deviations from rational, forward-looking behavior such as present bias (Angeletos, Laibson, Repetto, Tobacman and Weinberg, 2001; Parker, 2017; Laibson, Maxted and Moll, 2021);[2] and 'rational', considering liquidity constraints, taking as given rational and forward-looking behavior (Zeldes, 1989; Deaton, 1991; Carroll, 1997; Kaplan and Violante, 2014).[3] Which prevails has implications for policy: if a consumer is rational and forward-looking, easing their liquidity constraint raises their welfare; if they are present-biased, that could lower it.[4]

With typical cash stimulus, in the order of $1,000, it can be difficult to distinguish empirically between these explanations. In this paper, we leverage high-frequency bank-transactions and administrative data to study the effects of a very large and unexpected liquidity shock to a broad swath of the population. During the COVID-19 pandemic, the Australian government for the first time allowed eligible individuals to withdraw up to A$20,000 (US$13,600)[5] across two tranches from their mandatory private retirement savings accounts ('Superannuation', or 'Super'), normally inaccessible until retirement.[6,7] This was a large, optional, and direct transfer from a withdrawer's future self: the maximum withdrawal

[1] Examples include Agarwal and Qian (2014), Broda and Parker (2014), Parker, Soulless, Johnson and McClelland (2013), Sahm, Shapiro and Slemrod (2010), Shapiro and Slemrod (2009), and Johnson, Parker and Souleles (2006). These studies find high marginal propensities to consume or spend, out of fiscal transfers in the order of US$1,000, of 0.2–0.8 within six months. These responses tend to be higher among those on lower incomes, or those with low liquidity conditional on income. Recently, several studies have documented similarly large responses to transfers received during the COVID-19 pandemic, including Chetty, Friedman, Hendren and The Opportunity Insights Team (2022), Yannelis and Amato (2022), Karger and Rajan (2021), Kubota, Onishi and Toyama (2021), Baker, Farrokhnia, Meyer, Pagel and Yannelis (2020*b*), Baker, Farrokhnia, Meyer, Pagel and Yannelis (2020*a*), and Coibion, Gorodnichenko and Weber (2020).

[2] One alternative behavioral explanation to present bias is that of Pfäuti, Seyrich and Zinman (2023), who observe that a subset of people exhibit persistent over-confidence in their abilities and over-optimism about their future incomes, which generates similar behavioral implications to present bias (though with some different policy implications).

[3] Campbell and Mankiw (1989) characterize the aggregate consumption response as being due to heterogeneity across Ricardian and hand-to-mouth types. Garcia, Lusardi and Ng (1997) present early empirical evidence of heterogeneity, pointing both to liquidity constraints and behavior as key factors.

[4] Maxted (2022) finds the welfare cost of present bias is equivalent to a consumption tax of up to 17.2%.

[5] All figures are in Australian dollars unless otherwise stated. As of 2021, in PPP terms, US$1 bought A$1.45.

[6] We estimate at least 70% of working-age people were eligible to withdraw under the program.

[7] We know of two papers on this program. Sainsbury, Breunig and Watson (2022) use the same admin data to study the effect of program participation on employment outcomes. Wang-Ly and Newell (2022) study the program using coarser and more limited data (e.g., monthly, no admin data) from an Australian bank, but find a similar association between poor pre-treatment financial health and withdrawal, and a large spending response.

(which was the modal amount) by a modal-aged withdrawer can be expected to reduce their balance at retirement by more than $120,000 in today's dollars.[8] In practice, one in six working-age people (one in four 34-year-olds) participated, withdrawing $38 billion (2% of GDP). The average withdrawal was 51% of the available balance.

The Super withdrawal program had two unique features, which frame our analysis. First, they were optional.[9] This generates a selection effect, altering the mix of types relative to the population and thereby the consumption response relative to standard cash stimulus. Because withdrawals could effectively be re-contributed pre-tax (implying a subsidy of up to $7,528 depending on income and existing voluntary contributions), even 'Ricardian' types, who are rational, forward-looking, and liquid, had an incentive to participate.[10] Moreover, withdrawals may have relieved the liquidity constraints of 'rational hand-to-mouth' (RHTM) types, allowing them to smooth consumption or rebalance their portfolios towards higher-liquidity assets. On the other hand, people may have faced frictions, such as the mechanism proposed by Attanasio, Kovacs and Moran (2020) in which RHTM types choose low liquidity as a commitment device. Overall, it is not clear *ex ante* whether we should expect selection to have raised or lowered the MPC. We study a rich set of withdrawer characteristics to investigate this selection process.

The second feature is size.[11] Leading consumption models generate distinct predictions of how the consumption response changes as transfer size increases: Kaplan and Violante (2014) predict that raising the transfer from $500 to $5,000 would lower the MPC of the RHTM types from 0.20 to 0.03, whereas Laibson et al. (2021) predict the MPC of the behavioral types would fall only from around 0.13 to 0.11.[12] Given small transfers, which are typical, it is difficult to distinguish between the RHTM and behavioral types, who exhibit a similar propensity to consume. As the transfer size rises, however, the two responses diverge. As the modal Super withdrawal was nearly triple the amount in the example above, they generated substantial 'power' to distinguish between types. And because the withdrawals were a liquidity shock, holding lifetime income roughly constant, they served as a cleaner test of the PIH than other large shocks considered in the literature (e.g., lotteries). We estimate the spending response and interpret it through a heterogeneous-agent model, which confirms this intuition.

We begin by using administrative records covering the entire working-age population and a large panel of weekly bank transactions to study selection into the program to gauge the intensity of desire for liquidity and its predictors. We find the vast majority remained

[8] Based on historical 30-year net returns of 8.3%, average inflation of 2.5%, and a retirement age of 65.

[9] Note, under pure Ricardian equivalence, cash stimulus and Super withdrawals have identical opportunity costs because cash stimulus can be contributed to Super and attract the same net return.

[10] People could contribute pre-income-tax an additional $25,000 per year at a concessional tax rate of 15%. More than 99% of people were below this cap. Above that amount, re-contributions could be made post-income-tax.

[11] Song and Song (2023) study consumer responses to anticipated income changes in South Korea, finding that the MPC declines monotonically with an increase in income change.

[12] Levels are not directly comparable across the two papers.

constrained even after having accessed roughly half median annual wage income in additional liquidity: five in six withdrew as much as possible, nearly half withdrew in the first 10 days, and three quarters who had funds remaining after the first round withdrew a second time. Those in 'blue-collar' occupations and those located farther from urban centers were much more likely to withdraw. Withdrawers had slightly lower wages, but this was persistent rather than transitory: wages were lower during the two months prior, the three years prior, and the working life to date, and there was no discontinuity in weekly wages at the time of withdrawal. But withdrawers had radically lower rates of saving and levels of savings, both immediately prior to withdrawal and in the three years prior, and they had substantially lower stock and investment property holdings. These features were particularly pronounced among those who withdrew earlier or withdrew a second time, indicating a strong desire for liquidity among those with these characteristics.

Then we study the effect of the program. Using modern difference-in-differences techniques (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021) and exploiting the differential timing of withdrawal, we find a high MPX out of the first withdrawal of at least 0.43 (0.01) over eight weeks,[13] spread broadly across categories and with at least 60% of discernible spending on non-durables. Of this total spending response, 71% occurred within the first two weeks and 90% within four weeks. The MPX out of the second withdrawals was higher at 0.48 (0.01), which two-thirds returned for and which occurred after activity had recovered. Applying quantile difference-in-differences to compare withdrawers' and non-withdrawers' spending changes, we find that the MPX was near-uniformly distributed up to a value of 0.95 (with no excess mass at zero) with a long right tail (5% had an MPX of greater than one and 1% greater than 2.7). Among withdrawers, there were strong negative relationships between the MPX and several measures of pre-withdrawal financial health, and strong positive relationships with pre-withdrawal gambling and cash withdrawal. The least-liquid 40% spent more than double that of (around $2,500 more than) the most-liquid 20%.

Finally, to interpret our results, we develop a heterogeneous-agent model with two assets, income risk, and borrowing constraints in the spirit of Kaplan, Moll and Violante (2018), but with the inclusion of naively present-biased households, as in Laibson, Maxted and Moll (2022). We calibrate the economy to the sub-population of withdrawers in Australia at the monthly frequency, with the MPC defined as 60% (our estimated lower bound on the share of non-durables in the total spending impact) of the MPX.

With only liquidity-constrained but exponential-discounting households, the model cannot match the evidence. These households smooth the large transfers excessively even if they are at their borrowing limit. With impatient households (very-high-but-still-exponential-discounting), the model can only match the average observed MPC, and not the observed

[13]Excluding debt repayments and external transfers, which will have accounted for additional spending.

heterogeneity in MPCs and liquidity, and with an unrealistically low subjective discount factor (0.15 annually). We obtain the best fit to the data with naively present-biased households. Our calibrated present-bias parameter ($\beta = 0.58$) is of a similar magnitude to recent estimates (e.g., Ganong and Noel (2019); Gerard and Naritomi (2021)). In this case, households spend a large fraction of the liquidity injection within the first month. Not only does the model match the observed average MPC and average liquid assets-to-income ratio, but it also displays a joint distribution between liquidity and MPC that is close to its empirical counterpart.

The calibration frequency is critical. When calibrating at the annual frequency, the standard two-assets model with liquidity constraints and exponential discounting in fact successfully matches the evidence. However, this is misleading for two reasons. First, the observed increase in spending occurred within weeks of withdrawal (71% within two weeks; 90% within four). Second, at the annual frequency, the windfall represents a smaller fraction of income, which in turn increases the spending response. Our weekly spending data reveals a high-frequency spending impulse, which cannot be rationalized without present bias.

Our findings have direct implications for the design of private retirement saving systems, which have gained renewed interest as the US Social Security trust funds near depletion. The US 401(k) system is unique in its high degree of liquidity (Beshears, Choi, Hurwitz, Laibson and Madrian, 2015), loosened further during the pandemic. Under the Super withdrawal program, the vast majority of those who were eligible chose not to access their retirement savings when given a seemingly one-off opportunity to do so, while the vast majority of those who did appeared to be driven by present bias. Accordingly, as a matter of retirement saving policy, illiquidity would seem welfare-improving in aggregate, perhaps explaining its ubiquity in retirement saving systems outside the US (Fadlon and Laibson, 2022).

On the other hand, we find the policy generated at least 0.8% of GDP in direct additional spending, almost entirely within a four-month period. Based on the government's stated up-front fiscal cost of 0.06% of GDP, this implies a direct fiscal multiplier of 13.4, at least an order of magnitude higher than with cash stimulus (Ramey, 2019).[14] By generating a high MPX, the program raised the numerator; by being self-financed, it lowered the denominator. The government announced the fiscal cost as just $1.2 billion (reflecting foregone taxes over four years) and framed it as giving people access to "their own money". Given fiscal constraints (legal or political, as per Besley and Smart (2007)), self-financing can enable additional stimulus. This comes at the cost of the sub-optimal future consumption of the present-biased—though, that is also true of cash stimulus, which can be saved rather than spent. The question is whether macro-stability should be funded by the lower future retirement balances of the few or higher future taxes on the many, the consequences of which

[14]There are challenges in measuring comprehensively the fiscal multiplier (Nakamura and Steinsson, 2018, 2014). Our setting enables sharp identification of a direct increase in consumer spending in a short window of time driven by government policy, but we do not consider spillovers or other general-equilibrium consequences.

depend on the tax and transfer system.

To the best of our knowledge, the Super withdrawal program is unique in the literature in generating very large transfers to a broad swath of the population, holding lifetime income constant. Studies of stimulus checks consider transfers in the order of US$1,000, the responses to which should not differ markedly between the behavioral and RHTM types. Transfers from the Alaska Permanent Fund are larger (US$3,900 for an average family), but still far smaller than Super withdrawals (up to US$27,000 for a family) and received regularly (Hsieh, 2003; Kueng, 2018). Lottery winnings are the largest transfers considered in the literature, but they increase lifetime income substantially (Imbens, Rubin and Sacerdote, 2001; Kuhn, Kooreman, Soetevent and Kapteyn, 2011; Fagerang, Holm and Natvik, 2021).

The one direct policy precedent we know of occurred in Denmark in 2009, studied by Kreiner, Lassen and Leth-Petersen (2019). There are some important differences between their setting and ours. The Danish system was relatively new and small: it was introduced 11 years earlier and had been closed to contributions for five years (vs 27 years earlier and ongoing for Super); contributions were 1% of earnings (vs 10.5% for Super); and all savings received the same, flat return subject to income taxes on withdrawal (vs no taxes on withdrawal and other tax concessions for Super). Consequently, after taxes, the average withdrawal was US$1,900, an order of magnitude lower than the modal Super withdrawal of US$13,600. The authors combine survey data on spending with administrative data on assets to establish a relationship between liquidity-constraint tightness, as measured by the marginal interest rate, and spending. In contrast, our focus—aided by rich, high-frequency administrative and bank transactions data as well as unique features of the Super withdrawal program—is on *why* there is an association between liquidity and spending.

In that respect, we contribute to an emerging literature covering a variety of settings in which high-frequency spending data reveals an excess sensitivity of spending to income that can only be rationalized by present bias. Ganong and Noel (2019) consider the exhaustion of unemployment benefits in the US, documenting a non-durables spending reduction of 12%, consistent with a substantial share of recipients being present-biased ($\beta = 0.5$). Gerard and Naritomi (2021) consider São Paulo, Brazil, where workers laid off without cause are entitled to severance of 4.7 months' wages on average, estimating a spending increase of 35% despite a permanent-income decline of 14%, consistent with present bias ($\beta = 0.44$ in the naive case). Gelman (2022) reaches a similar conclusion based on spending responses in the US to regular paycheck (and tax-return) receipts. In a very different setting—with a very large, optional transfer going to almost a quarter of all 34-year-olds, and with concomitant continuity in personal circumstances, including wages and lifetime income—we present evidence that leads to strikingly similar conclusions. Our evidence suggests present bias is quite common.

Accordingly, we contribute to the literature on present bias (Cohen, Ericson, Laibson and White, 2020). For example, in an observational setting covering more than 70% of the

working-age population, we study the removal of a binding savings constraint—the opposite of the randomized controlled trial of Ashraf, Karlan and Yin (2006) in which people could *take up* such a constraint. We also contribute to the literature on retirement saving, in particular to studies on early withdrawals, including Goda, Jones and Ramnath (2022), Coyne, Fadlon and Porzio (2022), Goodman, Mortensen, Mackie and Schramm (2021), Andersen (2020), Beshears, Choi, Harris, Laibson, Madrian and Sakong (2020), and Argento, Bryant and Sabelhaus (2014).

We proceed as follows. In Section 2, we describe the policy context and data. In Section 3, we investigate the intensity of desire for liquidity along three dimensions: whether people withdrew; how early they withdrew; and whether they withdrew a second time. In Section 4, we estimate the spending responses to each withdrawal and how it was allocated across categories. In Section 5, we consider heterogeneity in the response. In Section 6, we develop and calibrate a heterogeneous-agent model to compare our results to predictions under different consumption models. And in Section 7, we conclude.

2 Preliminaries

2.1 Policy

Australia has a compulsory, defined-contribution private retirement saving system called Superannuation (or 'Super').[15] All employers are required to contribute an additional 10.5% of pre-tax wages to their employees' Super accounts, inaccessible outside exceptional circumstances until age 58 if retired or 65 if still working. The median pre-withdrawal balance by age is shown in Table 1.

For most people, Super is tax-preferred relative to other forms of saving (except the primary residence): employer contributions are made pre-income-tax, and only taxed at 15% when they enter the fund (compared to a modal marginal income tax rate of 34.5% and a top rate of 47%); before retirement, Super cash returns are taxed at 15% and capital gains at 10%; and neither returns generated in retirement nor withdrawals are taxed at all. Additional voluntary contributions of $27,500 per year before tax and $100,000 per year after tax are allowed, but less than 1% of people are above the pre-tax cap.[16] The median growth fund had an annual return net of fees and taxes of 9.5% over 10 years and 8.3% over 29 years.[17]

On March 22, 2020, during the initial COVID-19 outbreak, the Australian government announced eligible people could withdraw up to $10,000 from their Super accounts by June 30, followed by another $10,000 from July 1, the first time broad early access had been

[15] A more detailed description with references can be found in Appendix A.

[16] See Chan, Morris, Polidano and Vu (2022) for a study of the income and saving responses to these concessions.

[17] People can choose between portfolios within their Super fund based on risk. Most people keep their savings in a 'growth' fund for most of their working life (generating higher average returns but greater volatility) and then switch to a more conservative fund near retirement.

Table 1: Median Super balance by age

Age	Median balance ($)
20	3,264
30	34,908
40	82,208
50	124,146
65	207,071

Data: Australian Taxation Office
Note: Balances as at June 30, 2019.

granted. Notably, the government eschewed the universal cash transfers employed in other countries during the pandemic and which an Australian government of the opposite major party had implemented during the Global Financial Crisis.[18] Cash transfers were limited to lump-sum payments for those receiving government benefits, alongside wage subsidies and supplemental unemployment insurance payments.

Announcing the program, the then-Prime-Minister said it would "help Australians access more of their own resources to get through this time of crisis".[19] The government stated the fiscal cost as $1.2 billion, which reflected only foregone taxes over four years (not the $38 billion eventually withdrawn).[20] The government would later add broad eligibility conditions.[21,22] Applications for the first round opened around a month later on April 20 via the 'myGov' online portal. Applicants were to nominate a withdrawal amount and a reason for withdrawing, self-assessing eligibility. Applications were processed in three days on average, at which time the withdrawal was deposited into the applicant's bank account.[23]

Australia's experience of the COVID-19 pandemic was in general milder than many comparable countries'.[24] Australia was early to close its borders and international travel remained virtually impossible for non-citizens—and highly restricted for citizens—for the first 18 months. From March 28, all international arrivals were required to complete two

[18]Leigh (2012) found that program generated an MPX of 0.41–0.42 out of $950 checks.

[19]https://www.smh.com.au/politics/federal/a-support-package-built-on-debt-and-hope-but-approach\-must-change-20200322-p54cpa.html

[20]https://ministers.treasury.gov.au/ministers/josh-frydenberg-2018/media-releases/supporting-australian-workers-and-business

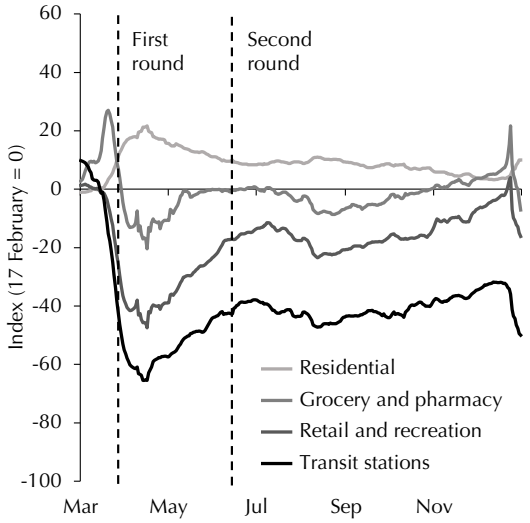
[21]This included those who: were unemployed; were in receipt of certain government benefits (e.g., unemployment insurance); had been made redundant or had their working hours reduced by at least 20% on or after 1 January 2020; were a sole trader whose business was suspended or had experienced a reduction in turnover of at least 20%; or were on a temporary visa and met certain conditions (e.g., not being able to meet immediate living expenses). In Appendix B, we construct an eligibility proxy suggesting more than 70% were eligible.

[22]https://treasury.gov.au/sites/default/files/2020-04/Fact_sheet-Early_Access_to_Super.pdf

[23]https://www.apra.gov.au/covid-19-early-release-scheme-issue-36

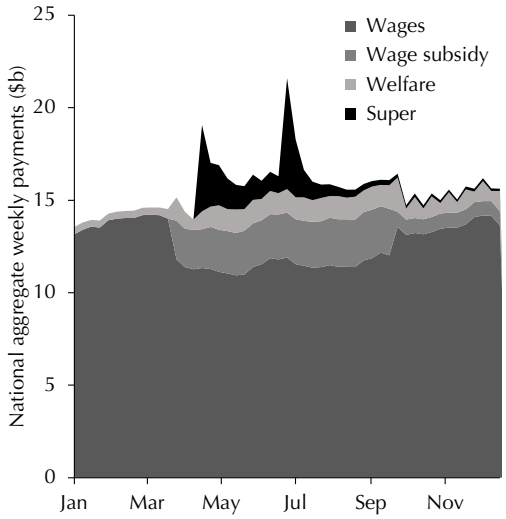
[24]For an overview of Australia's COVID-19 experience, see: https://independentcovidreview.com/wp-content/uploads/2022/10/FAULT-LINES-1.pdf.

Figure 1: Economic activity indicators in Australia during 2020



(a) Mobility indicators by establishment

Data: Google trends
Note: Google mobility data records physical locations people have visited.



(b) Working-age payments by type

Data: Australian Taxation Office and Department of Social Services

weeks of hotel quarantine. Public health measures were imposed in local areas until cases were eliminated. Australia's per-capita death rate was less than a tenth that in the US.[25]

Meanwhile, Australia had a relatively large federal fiscal response at 17% of GDP (excluding 2% of GDP in Super withdrawn). The Super withdrawal program was part of the second of three rounds of fiscal support announced during March 12–30.[26] While the initial outbreak generated a substantial reduction in mobility, this recovered rapidly as cases were eliminated (Figure 1a), and the decline in personal net income excluding Super withdrawals was negligible (Figure 1b). Through May and June, all domestic restrictions had lifted nation-wide.[27] In this context, the Super withdrawal program can be viewed as 'additive' relative to pre-pandemic personal net income, supported as it was by public health measures and fiscal transfers, pushing it well above its pre-pandemic level (Figure 1b).

2.2 Data

We rely on two data sources: administrative data covering all working-age Australians, which allow us to study the withdrawals; and bank transactions data covering a subset of

[25] https://ourworldindata.org/covid-deaths

[26] Hamilton (2020) compares the Australian and US fiscal responses. Breunig and Sainsbury (2023) consider the distribution of all fiscal transfers. Bishop and Day (2020) and Watson, Tervala and Sainsbury (2022) find Australia's wage subsidy program had a substantial effect on employment.

[27] https://www.aph.gov.au/About_Parliament/Parliamentary_Departments/Parliamentary_Library/pubs/rp/rp2021/Chronologies/COVID-19StateTerritoryGovernmentAnnouncements#_Toc52275795

working-age Australians, which allow us to study how the withdrawals were used. We are not permitted to link individuals across the two datasets, instead using each for different parts of the analysis, as noted. On the measures we observe in both datasets, including state, sex, welfare receipt, and the wage distribution, they appear quite similar (Appendix C). Elias (2022) presents evidence high-frequency spending records in the bank transactions data closely match those from other sources, including official statistics.

We access the administrative data via the Australian Bureau of Statistics' Multi Agency Data Integration Project (MADIP), which links de-identified, individual-level datasets across agencies. For our purposes, these cover all working-age (16–65) Australians who reported positive Super balances in the financial year before the pandemic (July 1, 2018 to June 30, 2019, or 2018-19), which yields a sample of 15.2 million (versus 25 million in the population).

In MADIP, we observe age, sex, and location at the suburb level. Via personal tax records, we observe: occupation; a spouse indicator; the number of dependents; three years of tax returns, including the income derived from wages, interest, rent, and dividends;[28] the Super balance at June 30, 2019; all Super contributions for 2018-19; and all information on the Super withdrawal program for all 4.5 million approved applications,[29] including the withdrawal amount, date, and the reason. Via the Single Touch Payroll system, we observe all weekly pre-tax wages. Via the welfare payment system, we observe all weekly government benefits, including unemployment benefits and pandemic support payments. We also observe all fortnightly wage subsidies each worker's employer received.

The bank transactions data are provided by Illion, one of Australia's three large credit bureaus. Data are collected during credit-check events initiated by Illion clients, including telcos, utilities, and financial institutions (more than 6,000 in total). When an individual triggers a credit-check event, Illion collects all bank transactions across their accounts, including transactions made with associated debit and credit cards, over the prior 13 weeks. In cases where multiple credit-check events are triggered by a single individual, the transactions data are stitched together to provide a longer transaction history. The original transactions data collected by Illion include the date and time the transaction was processed (usually within a few business days for card purchases and instantly for transfers), the description of the transaction, the type of transaction (e.g., card payment, direct debit, external transfer), the transaction value, and the account on which the transaction occurred.

The dataset we use is an aggregated version of this transaction-level data. Transactions are classified by Illion into spending categories (e.g., supermarkets, retail, department stores) and income categories (e.g., wage income, Super withdrawal, welfare income) using the

[28] Interest income is third-party reported by banks and financial institutions. Rental income is self-reported, though there may be strong incentives to report at least something because net rental losses may be claimed against other sources of income. Dividends are self-reported, though there is a strong incentive to report as tax paid at the corporate level may be credited against the personal tax liability on dividends.

[29] 3.05 million people lodged 4.78 million applications, of which 232,000 were rejected.

transaction description and type. External transfers initiated by the individual are not counted towards spending. For privacy reasons, single transactions are aggregated into weekly transaction amounts across all accounts for each spending and income category. This results in an individual-level panel of weekly spending and income by category, with a 13-week observation window for each individual ending at their credit-check event.

Observing a limited window for each individual introduces the possibility of assigning someone who withdrew Super before the start of their window as not having withdrawn. For the sample of withdrawers in the first round, we exclude those who: 1) did not have a recorded Super withdrawal, and 2) had an observation window that began after April 19 (the week preceding the first withdrawals). The second Super withdrawal sample was constructed identically, but relative to June 21. Among those we do observe having withdrawn super, we drop those for whom we do not observe three weeks of pre-withdrawal data. For the first round of withdrawals, we do not consider transactions beyond June 28 to avoid contamination by the second round. No other modifications were made to the data for the main analysis. This generates samples of around 340,000 and 410,000, respectively.

3 Withdrawal

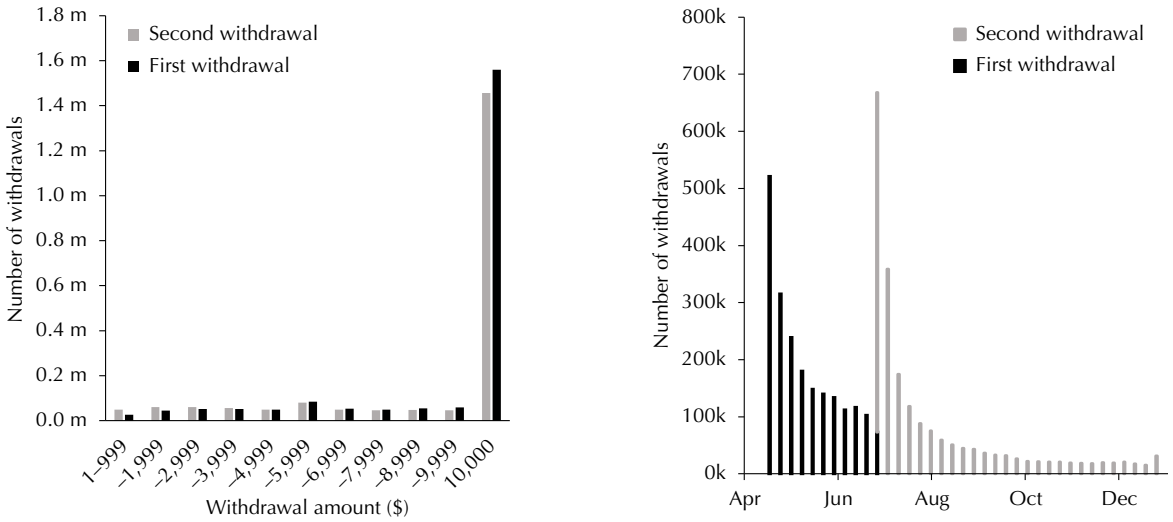
3.1 Withdrawers v non-withdrawers

We begin with some basic facts about withdrawal under the program. Around one in six (2.6 million) working-age people participated in the program, withdrawing $37.8 billion (around 1% of assets or 2% of GDP). Including those who did not withdraw, the average withdrawal was 9% the available balance; among just those who did withdraw, it was 51%. Around three quarters in each round withdrew the maximum $10,000, with the modal withdrawal across the two rounds $20,000 and the average $13,584 (Figure 2a). Among those who withdrew less than $10,000 in the first round, one third drained their account, suggesting they were constrained by their available balance. This means only around one in six chose an 'interior' withdrawal amount. Around three quarters of those who still had a positive balance remaining after withdrawing in the first round withdrew again in the second round, with the pattern of withdrawal amounts similar to the first round (Figure 2a). In the two rounds, 25% and 30% withdrew within the first three days and 40% and 48% within the first 10 days (Figure 2b). Collectively, these observations suggest the vast majority remained constrained even after having withdrawn up to $20,000 of their retirement savings (or $40,000 for a household with two withdrawing members).

Next, we compare the pre-withdrawal characteristics of those who participated in the program and those who did not.[30] In the first column of Table 2, we present estimated

[30]While withdrawal was subject to the eligibility criteria described earlier, eligibility was self-assessed. As

Figure 2: Number of withdrawals



(a) Number of withdrawals by amount

Data: Australian Taxation Office

(b) Number of withdrawals by week

Data: Australian Taxation Office

means among the non-withdrawers, and in the remaining columns we present estimated differences in means between the withdrawers and non-withdrawers, with the third through fifth columns including controls for pre-treatment wages and then cumulatively for the variables listed under 'Demographics'. Those who withdrew were on average three years younger, five percentage points more likely to be male, 12 percentage points more likely to be single, and eight percentage points more likely to have dependents.

In understanding the motivation for withdrawal, we are particularly interested in withdrawers' financial circumstances. Those who withdrew had lower wages, both during the month before withdrawals commenced (3% lower) and during the three years before (8% lower). We find no change in individual-level weekly wages coincident with withdrawal.[31] Withdrawers had around half the Super balances of non-withdrawers, which mechanically reflects lower wages over the working life to date.[32,33] Collectively, these observations indicate the difference in wages was persistent, being present in the month prior, the three years prior, and the working life to date.[34] Because the withdrawers were not on average suffering a temporary wage shortfall, this does not seem a likely motivation for withdrawal.

There were much larger differences in the levels of financial assets. In the month prior to

discussed in Appendix B, we estimate at least 70% were eligible, and conditioning on eligibility doesn't alter meaningfully any of the patterns observed in Table 2.

[31]This is based on an event study on wages using the same method we apply to spending later (Appendix D).

[32]Compulsory Super contributions are a flat rate of wage earnings and voluntary contributions are small.

[33]Additionally, the Super balance and wage densities among the withdrawers were compressed, with those in the middle over-represented (Appendix E).

[34]This persistence of lower wages is consistent with Parker (2017), who relates it to the MPC.

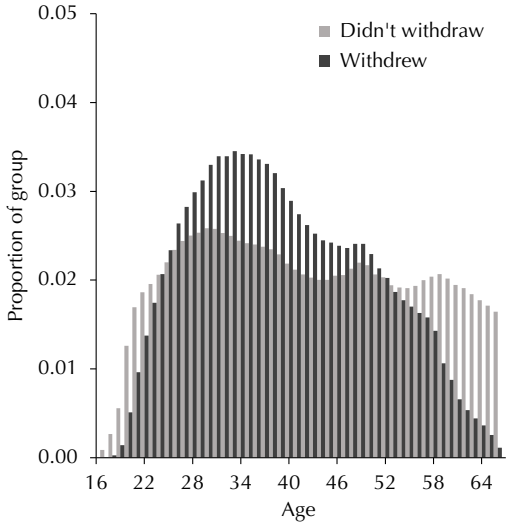
Table 2: Estimated differences in means between withdrawers and non-withdrawers in the first round

	Non-withdrawer	Withdrawer (difference)				
Controls	None	None	Wages	Plus age	Plus all	*Data*
Demographics						
Age	41.09	-2.68	-2.09			A
	(0.00)	(0.01)	(0.01)			
Female	0.49	-0.05	-0.08	-0.07		A
	(0.00)	(0.00)	(0.00)	(0.00)		
Had spouse	0.57	-0.12	-0.09	-0.06		A
	(0.00)	(0.00)	(0.00)	(0.00)		
Had dependents	0.38	0.08	0.09	0.10		A
	(0.00)	(0.00)	(0.00)	(0.00)		
Long-term financials						
Annual wage income	47,340	-4,050				A
	(15)	(35)				
Super balance	121,398	-61,237	-48,383	-35,882	-34,520	A
	(66)	(157)	(143)	(133)	(134)	
Interest income	420	-314	-306	-258	-261	A
	(1)	(2)	(2)	(2)	(2)	
Rental income	958	-369	-296	-240	-229	A
	(1)	(3)	(3)	(3)	(3)	
Dividends	1,106	-857	-809	-657	-669	A
	(4)	(10)	(9)	(9)	(9)	
Voluntary Super	2,467	-2,199	-2,159	-1,692	-1,637	A
	(4)	(11)	(11)	(11)	(11)	
Short-term financials						
Weekly wage income	786	-21				B
	(2)	(7)				
Saving / spending	0.37	-0.20	-0.22			B
	(0.01)	(0.03)	(0.03)			
Savings / spending	5.38	-3.31	-3.34			B
	(0.07)	(0.25)	(0.25)			
Debt payment / spending	0.14	0.01	0.01			B
	(0.00)	(0.00)	(0.00)			
Had negative balance	0.09	0.02	0.02			B
	(0.00)	(0.00)	(0.00)			

Data	N
A: Administrative data	15,249,488
B: Bank transactions data	336,809

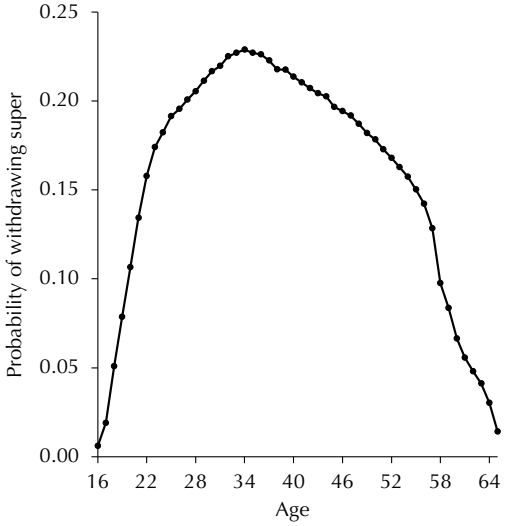
Data: Australian Taxation Office and Illion.
Notes: Results are from simple linear regressions of outcomes on a binary first-withdrawal indicator, controlling cumulatively for wages and the 'Demographics' variables. Wage control for Demographics and Long-term Financials is average pre-tax wage income in the prior three years. Spouse and dependents are from the tax return in the financial year prior to withdrawal (July 1, 2018–June 30, 2019). Long-term financials except Super Balance and Voluntary Super are averages across the three prior tax returns (2016–17, 2017–18, and 2018–19). Super balance is as at June 30, 2019. Voluntary Super contributions are for the prior year (2018–19). Annual wage income is pre-tax and weekly wage income is post-tax. All short-term variables are averages for the month prior to program commencement. Standard errors in parentheses. All estimates statistically significant at the 95% level.

Figure 3: The relationship between withdrawal and age



(a) Age histogram by withdrawal status

Data: Australian Taxation Office
Note: Sample includes those with a positive Super balance.



(b) Probability of withdrawal by age

Data: Australian Taxation Office
Note: Sample includes those with a positive Super balance.

withdrawal, the withdrawers had a 54% lower saving rate, 62% lower bank balances relative to spending, a 23% higher probability of having an overdrawn account, and 10% higher debt repayments relative to spending—all robust to wage differences. There were similar differences over the longer term, with withdrawers having received 75% less interest income, 24% less rental income, and 60% less in dividends in the past three years. Withdrawers also made 89% lower voluntary Super contributions in the past year, reflecting that they were 10 percentage points (17.3% v 7.7%) less likely to have made any voluntary contribution, while those who did made 74% lower contributions on average ($3,327 v $12,766).

For some further context around the decision to withdraw, in Figure 3 we present the age distributions of the withdrawers and non-withdrawers along with the associated probability of withdrawal by age. As noted earlier, the withdrawers were three years younger on average, but this masks a compression of the age distribution among the withdrawers. The withdrawers were underrepresented up to age 23 and beyond age 51, with a modal age of 33.[35] The maximum take-up rate was among those aged 34, at 23%.[36][37]

In Table 3, we divide the Australian working-age population by occupation and location

[35]The underrepresentation up to age 23 was not due to a lower probability of having a positive Super balance because the observed population is conditional on that, but it may be explained by lower balances or a lesser degree of salience or attention among the youngest.

[36]This rises to 27% at an earlier age of 32 when we consider take-up only among the eligible (Appendix B).

[37]The drop in take-up at age 57 coincides with the age individuals could begin to access their Super if they were retired. Because those over 57 and retired could already access their Super, they had no reason to participate in the program.

Table 3: Withdrawal rates by occupation and location

	Withdrew (%)
Occupation	
Machinery operators and drivers	32.3
Laborers	30.5
Technicians and trades workers	24.4
Community and personal service workers	22.7
Sales workers	20.0
Managers	16.8
Clerical and administrative workers	15.4
Professionals	9.4
Location	
Very remote	24.2
Remote	21.1
Outer regional	19.5
Inner regional	18.1
Major cities	17.3

Data: Australian Taxation Office and Australian Bureau of Statistics
Note: Occupation based on tax return in prior financial year. Location based on suburb from combined administrative data.

and calculate withdrawal rates among these divisions.[38] There was strong variation in withdrawal along both dimensions. Withdrawal was highest in 'blue-collar' professions and lowest in 'white-collar' professions, with the lowest-withdrawing occupation teachers at 6.3% and the highest construction and mining laborers at 40.2%. Withdrawal was also strongly, monotonically, and negatively related to the proximity to cities, with those in very remote areas 40% more likely to withdraw than those in major cities. In the most remote locations, more than half of people withdrew. The communities with the lowest rates of withdrawal were in Canberra (Australia's capital), in the 3–5% range.

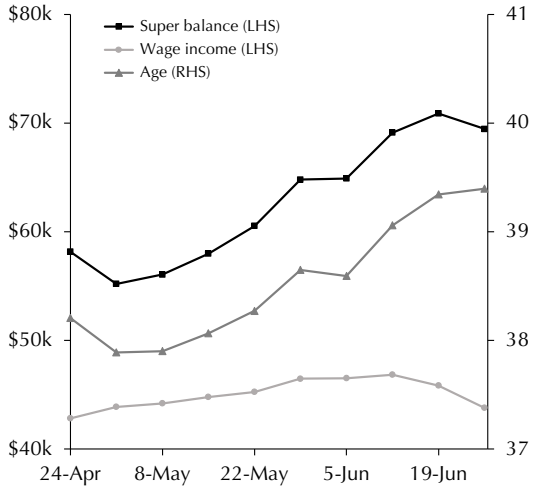
3.2 Timing

People faced not only a choice of whether to withdraw but also how soon to withdraw. The policy was announced around a month before applications opened, and funds were received within just a few days of application. In the first withdrawal, 25% of withdrawals occurred in the first three days, another 15% in the next seven days, and the remaining 60% over the following two months (Figure 2b).

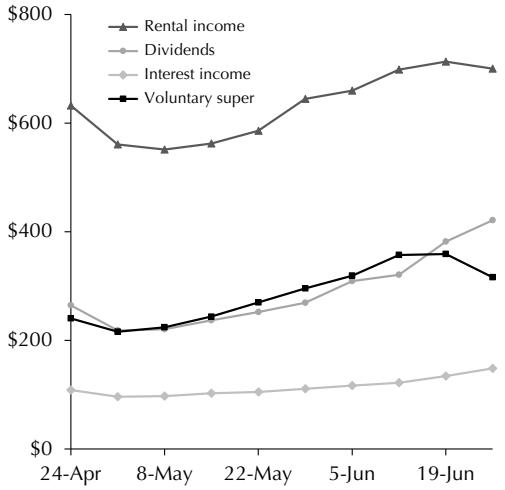
The differences between the withdrawers and non-withdrawers observed in Table 2 are greater the earlier the withdrawal occurred (Figure 4). Setting aside the first and last weeks, which may be subject to idiosyncratic factors, the average Super balance of a withdrawer

[38]Appendix F includes a full break-down of occupation into 46 categories.

Figure 4: Average characteristics by withdrawal week during the first round



Data: Australian Taxation Office
Notes: Outcomes as per 'Long-term financials' in Table 2.



Data: Australian Taxation Office
Notes: Outcomes as per 'Long-term financials' in Table 2.

increased by 28% over the intervening seven weeks, average wages by 4.5%, and average age by 1.5 years. Average pre-treatment interest, dividends, and rental income all increased with the withdrawal date, a relationship that remained statistically significant even after controlling for the characteristics conditioned on earlier (Appendix G). With the program having offered temporary access to ordinarily inaccessible wealth, the front-loading of withdrawals suggests a degree of urgency. The fact this urgency was strongly associated with asset levels (in particular, liquid assets) is consistent with our earlier findings for withdrawal generally. Overall, those with persistently less liquidity were more likely to seek additional liquidity—and to seek it sooner.

3.3 Second withdrawal

In addition to having a choice of whether and how soon to withdraw, people could also choose to withdraw a second time, 72 days after applications for first withdrawals opened. 54% withdrew in both rounds, 24% in only the first, and 21% in only the second. One advantage of observing the second withdrawal is that it came well after the initial pandemic shock, once it had become clear health and economic outcomes in Australia would be substantially better than originally feared. During May and June 2020, domestic restrictions eased nation-wide. While both rounds were announced in late May, the first round opened at the peak while the second round opened after activity had recovered substantially (Figure 1a). Observing whether people took a second opportunity to withdraw allows us to gauge the intensity of their desire for liquidity and the characteristics associated with it.

Table 4: Differences in means between those who did and did not withdraw a second time

	Withdrew first only	Withdrew first and second (difference)			
Controls	None	None	Wages	Plus age	Plus all
Wages	43,173	4,897			
	(54)	(64)			
Age	37.88	1.82	1.67		
	(0.01)	(0.02)	(0.02)		
Super balance	55,652	16,226	11,774	6,024	6,024
	(128)	(150)	(139)	(128)	(128)
Interest income	137	-30	-32	-40	-38
	(1)	(2)	(2)	(2)	(2)
Rental income	707	-43	-122	-160	-130
	(5)	(6)	(6)	(6)	(6)
Dividends	317	-43	-52	-87	-80
	(7)	(9)	(9)	(9)	(9)
Voluntary Super	394	-142	-161	-194	-190
	(4)	(5)	(5)	(5)	(5)
N = 1,862,516					

Data: Australian Taxation Office
Notes: Results are from simple linear regressions of outcomes on an indicator for withdrawing in the second round, controlling cumulatively for the wages and 'Demographics' variables listed in Table 2. Excluded from the regression are those who did not withdraw in the first round as well as those who did but drained their balance. Variable definitions as per 'Demographics' and 'Long-term financials' in Table 2.

Focusing on those who had a positive Super balance remaining after withdrawing in the first round, we observe similar characteristics among those who withdrew a second time as among those who withdrew at all or withdrew earlier (Table 4). Those who withdrew a second time did have higher wages, were slightly older, and had higher Super balances. But this is expected, as we removed those having drained their accounts in the first round, who were disproportionately lower-income, younger, and with lower Super balances. Even so, those who withdrew twice had 22% less interest income, 36% lower voluntary Super contributions, 14% less in dividends, and 6% lower rental incomes. And when we condition on wages and age, these differences increase substantially. Overall, those with persistently less liquidity were more likely to seek additional liquidity, to seek it sooner—and to seek it a second time.

4 Spending

4.1 Marginal propensity to spend

Our spending measure includes all merchant debits associated with an individual's bank accounts (such as with a debit or credit card), cash withdrawals, and 'buy now, pay later'

repayments. It excludes all debt repayments and external transfers from the accounts. In Australia, electronic methods cover the vast majority of consumer payments, with cash transactions having fallen from 40% in 2007 to 10% in 2019,[39] compared to 22% in the US.[40] And, in a 2019 official survey, just 12% of those who reported holding cash outside their wallet did so to fund a large purchase, suggesting cash withdrawals overwhelmingly are used for immediate consumption.[41] Because we exclude all debt repayments and external transfers, which account for additional spending, our estimates can be viewed as conservative lower bounds on the true spending responses.[42]

We begin by plotting average income and spending among all units in the bank transactions data by 2020 calendar week (Figure 5). We also split these aggregates into those who did and did not withdraw Super. The timing of each round is clearly visible in both income and spending in the aggregate. There is a sharp spike in income coincident with the first week of withdrawals in both late April and early July, and concomitant but more diffuse increases in spending. This mirrors closely the timing profile of withdrawals we observed in the administrative data in Figure 1b. Split into withdrawers and non-withdrawers, Super withdrawal is even clearer.

There are two issues with this aggregate view. First, as noted earlier, there were a number of concomitant income (and thus spending) shocks, including supplementary unemployment insurance with relaxed eligibility requirements and mutual obligations, a large-scale wage subsidy program, cash transfers to government benefit recipients, and tax refunds distributed from July, which explain the concomitant spikes in non-withdrawer income. Second, withdrawals occurred over many weeks within each round, with the calendar-based income and spending profiles aggregating potentially heterogeneous income and spending shocks across cohorts at different times relative to withdrawal.

Accordingly, we consider the effect of withdrawal on weekly income and spending in an event study, with the non-withdrawers serving as our comparison group (we address identification in the next subsection). We take the approach of Callaway and Sant'Anna (2021) and Sun and Abraham (2021) by estimating average treatment effects on the treated (ATTs) *separately* for each cohort (those who withdrew in a particular week) and then aggregate those ATTs across cohorts weighted by their size.[43] These methods address a range of potential

[39] https://www.rba.gov.au/publications/bulletin/2020/mar/pdf/consumer-payment-behaviour-in-australia.pdf

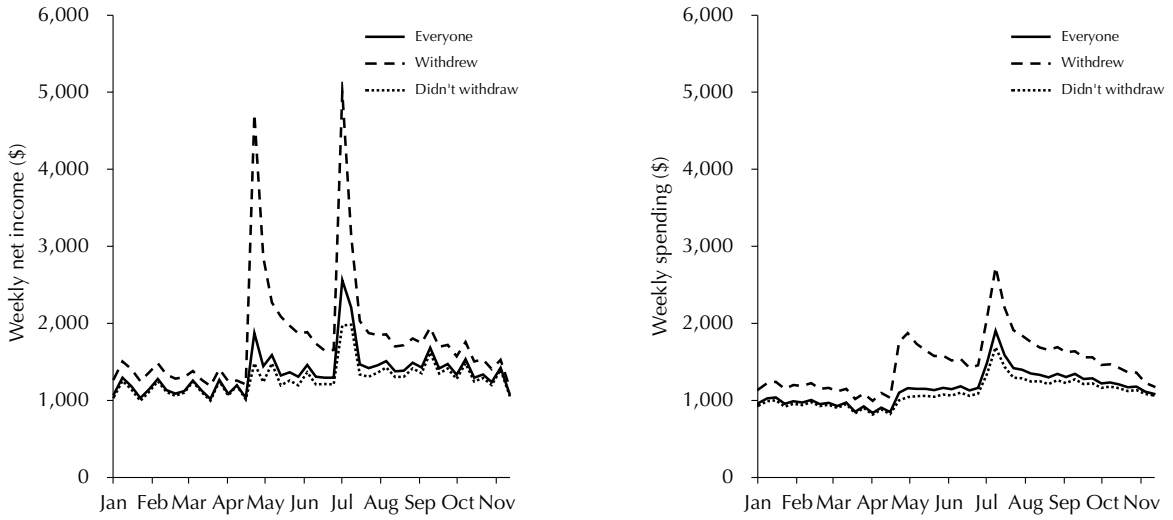
[40] https://www.atlantafed.org/banking-and-payments/consumer-payments/survey-of-consumer-payment-choice

[41] https://www.rba.gov.au/publications/bulletin/2020/jun/pdf/cash-use-in-australia-results-from-the-2019-consumer-payments-survey.pdf.

[42] We focus on the MPX rather than MPC because the bank transactions data cannot precisely be disaggregated into durables and non-durables. But we do observe spending categories likely to include only non-durables, which we consider later. Laibson et al. (2022) provide a theoretical mapping from MPCs to MPXs.

[43] In contexts such as ours, in which there is a never-treated group and an unconditional parallel trends assumption is made, these two methods are equivalent, as both pairs of authors note.

Figure 5: Average weekly income and spending in 2020 by group



(a) Income

Data: Illion

(b) Spending

Data: Illion

problems with the two-way fixed-effects estimator commonly used in event study designs (de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak, Jaravel and Spiess, 2022; Wooldridge, 2022).[44]

In Figure 6, we display cohort-specific event-study plots reflecting estimates of the following standard interacted TWFE model:

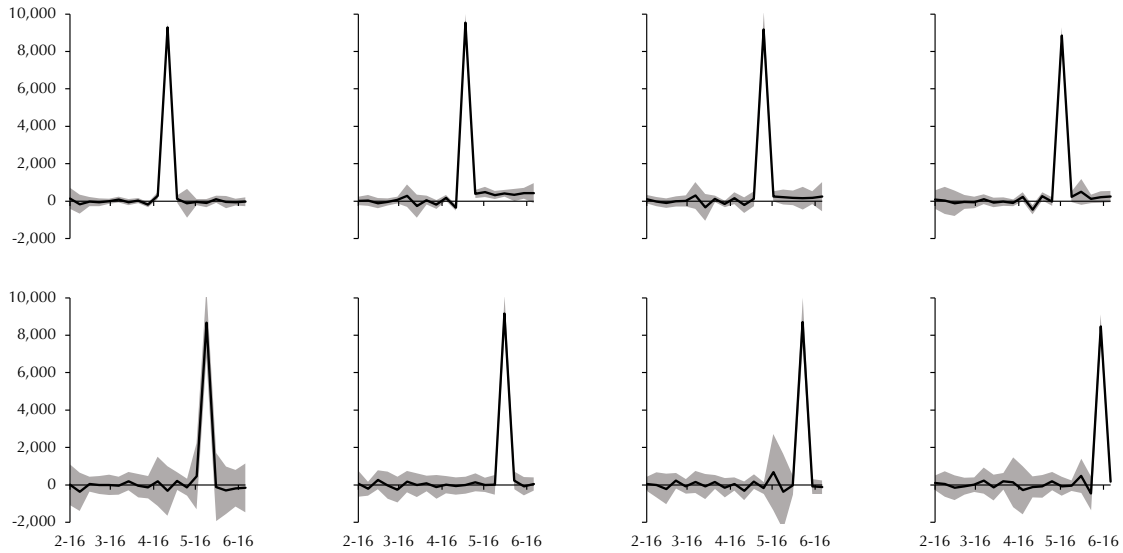
$$Z_{it} = \alpha_i + \lambda_t + \sum_{\ell \neq -1} \delta_{e\ell} \left(\mathbf{1}\{E_i = e\} \cdot D_{it}^{\ell} \right) + \varepsilon_{it},$$

where Z_{it} is the outcome for unit i in time t (either income or spending), α_i is an individual fixed effect that controls for all time-invariant unit-level characteristics, λ_t is a time fixed effect for each week, ℓ refers to event time (periods relative to treatment), e refers to the cohort receiving the treatment at a given time, E_i refers to the time when unit i receives the treatment, and D_{it}^{ℓ} is a treatment dummy. Never-treated units are coded as $D_{it}^{\ell} = 0$ in all periods. The method computes, *for each cohort*, the average difference across treated and never-treated units between the outcome in the current period and that in the period immediately prior to treatment, as in the canonical two-by-two difference-in-differences setup.

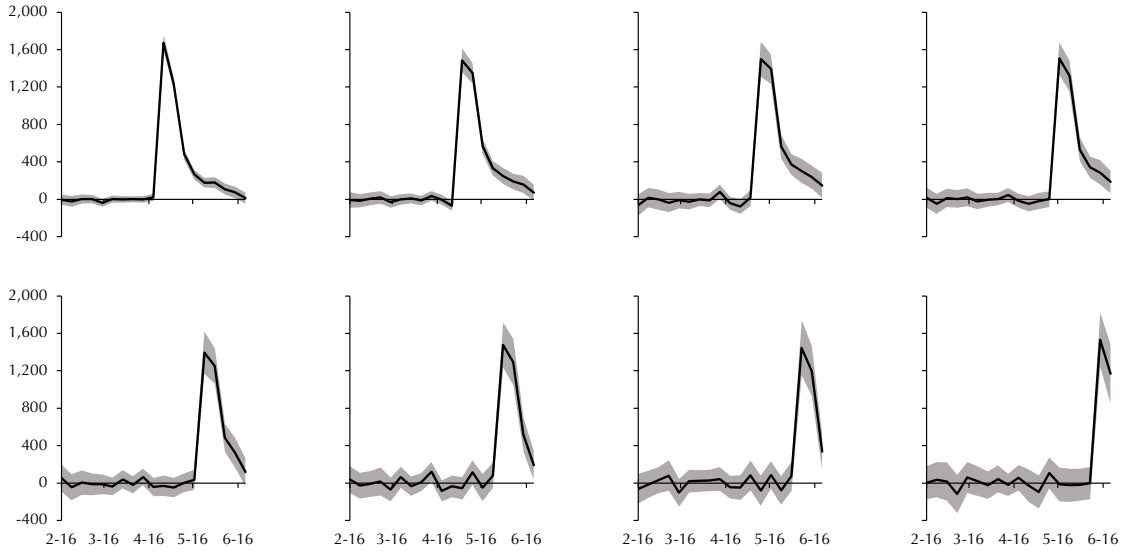
These weekly cohort ATTs may then be aggregated across cohorts to produce a single

[44]Of concern in this recent literature are situations in which: different units are treated at different times; there is no 'never-treated' group; there are heterogeneous treatment effects across cohorts; or time-varying controls are used. A key problem with standard TWFE regression arises from the implicit weights used to aggregate treatment effects across cohorts, which can in some cases be negative (Goodman-Bacon, 2021). For a review of these developments, see Roth, Sant'Anna, Bilinski and Poe (2022).

Figure 6: Estimated cohort ATTs ($) of the first withdrawal by calendar week



(a) Income



(b) Spending

Data: Illion
Notes: Results are cohort ATTs estimated via the R package, 'did', which implements Callaway and Sant'Anna (2021). Comparison group is the never-treated. Estimation is 'doubly-robust', with standard errors computed using the bootstrap procedure of Callaway and Sant'Anna (2021). Confidence intervals are at the 95% level. Cohorts 1 to 4 are displayed left-to-right in the top rows; cohorts 5 to 8 left-to-right in the bottom rows. Calendar time is truncated on the right to avoid contamination by the second withdrawals, beginning on July 1. The 'did' package, by default, uses a 'varying' base period when estimating cohort ATTs for the pre-treatment periods, where the base period is the period immediately prior. This is why estimates for the period immediately prior to withdrawal (and their confidence-interval estimates) are not zero. For all post-treatment estimates, the period immediately prior to treatment is used as the base period.

ATT for each period relative to treatment, using the cohort shares as weights: $\text{ATT}_\ell = \sum_e \delta_{e\ell} \cdot \Pr[E_i = e]$. Those estimates are displayed in Figure 7.[45] We then sum our ATTs across the post-treatment periods for which we observe a positive treatment effect on spending, which based on Figure 7b is eight weeks.[46] To construct the MPX, we need to divide our estimated cumulative aggregate spending ATT by the withdrawal amount.[47] But because non-super-withdrawal income may vary post-treatment between the withdrawers and non-withdrawers, instead we divide by the income analogue of our cumulative aggregate spending ATT:

$$\text{MPX} = \frac{\sum_{\ell=0}^{7} \text{ATT}_\ell^X}{\sum_{\ell=0}^{7} \text{ATT}_\ell^Y} = \frac{\sum_{\ell=0}^{7} \sum_{e=1}^{8} \delta_{e\ell}^X \cdot \Pr[E_i = e]}{\sum_{\ell=0}^{7} \sum_{e=1}^{8} \delta_{e\ell}^Y \cdot \Pr[E_i = e]},$$

where X is spending and Y is income.[48,49]

Our estimates are displayed in Table 5. Our estimated MPX of 0.43 over eight weeks is high in the context of estimates of the effects of far smaller cash transfers; Leigh (2012), for example, estimates an almost-identical MPX of 0.41–0.42 out of $950 stimulus checks distributed in Australia during the Global Financial Crisis (around a tenth the size of first withdrawals in our setting). Note that, because we exclude all debt repayments and external transfers, our estimate should be viewed as a conservative lower bound on the true spending impact. The income and spending shocks are also large relative to their pre-withdrawal levels. The first round of withdrawals raised income by 93% on average over eight weeks. In the month before withdrawal, the withdrawers spent $1,107 per week on average. Our estimates indicate spending was 129% higher over the first two weeks and 46% over eight weeks.

The sharpness of the spending impact, observable due to the high-frequency nature of our bank transactions data, is particularly notable. Leading studies of the spending impact of transfers have tended to focus on an annual or quarterly frequency due to data availability (e.g., Parker et al. (2013)). Broda and Parker (2014) show that two-thirds of non-durable

[45]The tight correlation between the TWFE and aggregate consumption paths following Super withdrawal (Figures 7 and 5), and our use of high-frequency consumption data, address issues with the US Great Recession stimulus literature raised by Orchard, Ramey and Wieland (2023).

[46]Appendix H includes estimated weekly cohort ATTs for income and spending.

[47]This is similar to Flynn and Smith (2022), who estimate the effect of Clean Water Act funding on capital investment by dividing the effect on average capital investment by the effect on average grant funding.

[48]While the 95% confidence interval for the estimated income ATT shown in Figure 7 contains zero, the weekly point estimates are modestly but consistently positive—evidently driven by a small but statistically significant and persistent increase in income for the second cohort, as can be seen in Figure 6a. Attributing all additional post-treatment spending to Super would upwardly bias our MPX estimate. But note that $9,191, or 94%, out of a total income increase of $9,940 over eight weeks is Super.

[49]Because we are dividing one estimate by another, we estimate standard errors via a bootstrap procedure. For a single bootstrap iteration, we construct a bootstrap sample by resampling individuals with replacement, then perform the difference-in-differences estimation procedure described on each subsample. Standard error estimates are the standard deviations of our estimates across 1,000 bootstrap iterations.

Table 5: Estimated cumulative aggregate ATTs

Outcome	First withdrawal	Second withdrawal
Income	9,343	10,314
	(294)	(274)
Spending	4,033	4,982
	(59)	(169)
MPX	0.43	0.48
	(0.01)	(0.01)
N	337,223	410,761

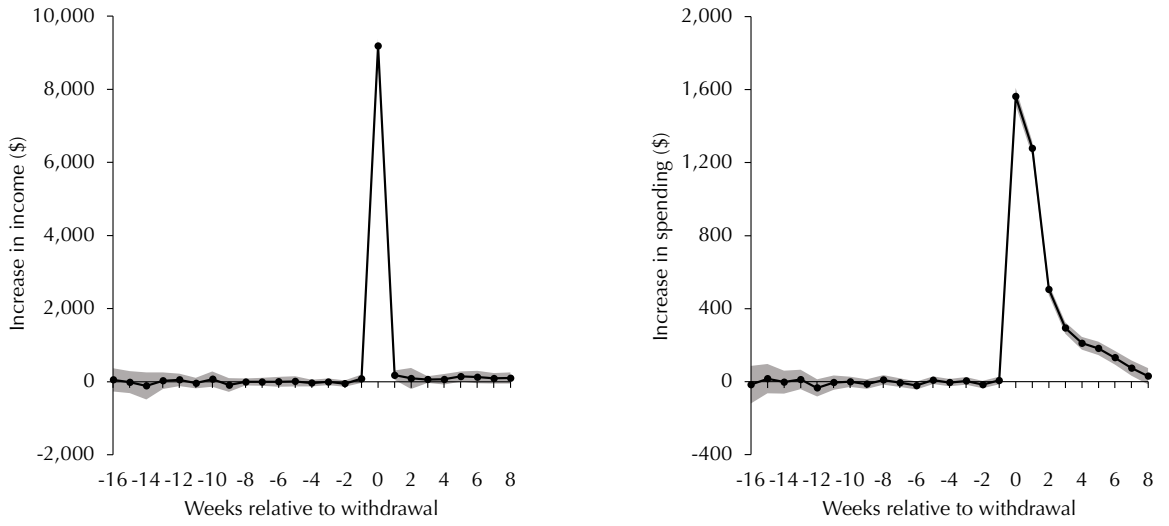
Data: Illion
Notes: Results are based on cohort ATTs estimated via the R package 'fixest' (estimates in Appendix H), which implements Sun and Abraham (2021). We compute weekly aggregate ATTs by averaging across cohorts weighted by cohort share and accumulate over the first eight post-treatment weeks. MPX is spending divided by income. All standard errors (in parentheses) are estimated via a standard bootstrap procedure.

expenditures driven by rebates in the US in 2009 occur within a month and Aladangady, Aron-Dine, Cashin, Dunn, Feiveson, Lengermann, Richard and Sahm (2023) show that Earned-Income Tax Credit recipients spend around 30% of their tax refunds within two weeks. In our setting, given a transfer an order of magnitude larger than in these prior studies, 39% of the total spending impact occurred within the first week, 71% within the first two weeks, 83% within the first three weeks, and 90% within the first four weeks. By the eighth week, spending had returned to its pre-withdrawal level.

Observing spending out of the second withdrawals allows us to probe further the intensity of the desire to spend and to assess the spending impact in a more plausibly externally valid context. By July, when second withdrawals began, public health restrictions had lifted nation-wide and case numbers had been reduced to zero, in stark contrast to the experiences in most countries. This may address concerns that the large observed spending impact of the first withdrawals was driven by panic or early pandemic-related spending. The estimated MPX for the second withdrawal was even higher at 0.48 with a similarly sharp spending profile (Appendix I).[50] Recall that three quarters of those who had a positive balance remaining after withdrawing in the first round chose to withdraw again. It is striking that for so many the desire to draw on retirement savings to finance immediate spending had not been exhausted by the first $10,000 withdrawal.

[50]If our spending estimates are representative of all withdrawals, the first and second withdrawals together generated 0.8% of GDP in additional direct spending, almost entirely within May–August 2020.

Figure 7: Estimated ATTs of the first withdrawal by event week



(a) Income

(b) Spending

Data: Illion

Notes: Results are averages of cohort ATTs in Figure 6 weighted by cohort size, estimated via the R package, 'did', which implements Callaway and Sant'Anna (2021). Comparison group is the never-treated. Estimation is 'doubly-robust', with standard errors computed using the bootstrap procedure of Callaway and Sant'Anna (2021). Confidence intervals are at the 95% level. The 'did' package, by default, uses a 'varying' base period when estimating cohort ATTs for the pre-treatment periods, where the base period is the period immediately prior. This is why estimates for the period immediately prior to withdrawal (and their confidence-interval estimates) are not zero. For all post-treatment estimates, the period immediately prior to treatment is used as the base period.

4.2 Identification

It is necessary to make a parallel trends assumption in order for our estimated ATTs to identify causal effects: that, following withdrawal, average income and spending among the withdrawers would have evolved similarly to those among the non-withdrawers had the withdrawers not withdrawn. This assumption does not require randomization of withdrawal nor even balance of observed variables across withdrawers and non-withdrawers. There are two potential threats to identification under this design: that withdrawers' and non-withdrawers' income or spending were on different trends leading up to withdrawal, or that the income or spending of only the withdrawers or non-withdrawers was subject to a confounding effect following withdrawal.

Note that, under our TWFE specification, we are making the comparison between the withdrawers and non-withdrawers conditional on all observed and unobserved time-invariant but group-specific and time-varying but common characteristics. This means the withdrawers and non-withdrawers can have very different incomes or spending so long as these differences are stable over time, and their incomes or spending can be subject to pandemic-related shocks so long as these are common to the two groups. Further, recall that we have addressed bias due to differential concomitant income shocks by dividing by our estimated cumulative aggregate income ATTs rather than the withdrawal amount.

In Figures 6 and 7, one can observe clearly the evolution of tightly parallel pre-trends in every cohort and all withdrawers overall, even without conditioning on additional, time-varying observed variables. There is also no evidence of anticipation by any cohort or overall, which supports identification but is also substantively interesting. The ability to withdraw was announced a full month prior to the first withdrawals and almost half of withdrawals occurred in the first 10 days. The absence of any anticipatory effect on spending is consistent with liquidity being a major constraint on spending among the treated.

Next, in Figure 6, there does not appear to have been any post-treatment confounder that, in calendar time, applied only to either the treated or never-treated groups. Moving between cohorts, the treatment date advances by one week, each income spike advances by one week, and each spending spike also advances by one week. The dynamic paths of income and spending were similar across cohorts, with spending consistently elevated over the first two weeks and then having tapered down similarly over the subsequent six weeks. This suggests against the occurrence of a confounding event affecting all cohorts on a given calendar date.

There remains a potential for a confounding effect only on treated or never-treated units at the time of treatment for each cohort; that is, in event rather than calendar time. Reverse causality is one possible manifestation of this: that the spending caused withdrawal rather than the reverse. This is a form of selection bias, as never-treated units switch to the treated group at the time of treatment. In order for this to be a major concern, given the large share

of the treated group in the population and the large treatment effect among that group, it would have to have resulted in a visible decline in spending among the never-treated group as those whose spending would have been elevated even in the absence of treatment selected out of the never-treated group, lowering spending there.

The aggregate spending in Figure 5 suggests this was not the case. Not only did spending among the never-treated not decline at the time of the first withdrawals, but spending in aggregate across all units (uncontaminated by selection bias as all units are present at all times) rose at a rate greater than would be explained by Super withdrawals alone. This was also the case at the time of the second withdrawals, addressing concerns this may have been due to early pandemic-related spending (e.g., panic buying or home office purchases) across both treated and never-treated groups. For additional confidence, in Appendix D we present the result of an event study on weekly wages, which one might not expect to be affected by withdrawal but may have been associated with selection, showing no effect concomitant with treatment.

There is also a question of external validity. It is worth emphasizing that our estimates are average treatment effects on the *treated*—those who withdrew. As shown earlier, the withdrawers differed markedly from the non-withdrawers; in particular, having had persistently poorer financial health. While this in and of itself does not threaten identification, or internal validity, to the extent it explained selection it may still have affected the spending induced by the program, and thus have implications for the external validity of the estimates. This effect is *ex ante* theoretically ambiguous because liquidity-constrained withdrawers may have accessed Super to finance spending or to rebuild liquidity. The very high spending we observe is consistent with the former (as is further evidence to come). But there is no suggestion this estimated MPX applies to the population broadly.

4.3 Spending categories

In Figure 8, we present estimated cumulative aggregate ATTs for each spending category we observe.[51] Spending categories are defined based on the merchant name (such as a large national chain or the merchant name containing a recognizable label). The largest share of spending was 'uncategorized'—in reality, this will have been spread across the other categories. ATM withdrawals constituted the other large category. Recall that Australia is mostly a cashless society, with cash accounting for just 10% of consumer spending. In a 2019 survey, just 12% of those holding cash outside their wallet did so to save for a large purchase, which suggests cash withdrawals were not only likely predominantly used for spending but spending predominantly on non-durables.[52] Also, we include debt repayments for scale,

[51] A corresponding table of results can be found in Appendix J.

[52] https://www.rba.gov.au/publications/bulletin/2020/jun/pdf/cash-use-in-australia-results-from-the-2019-consumer-payments-survey.pdf

though these are not included in our aggregate spending estimates.

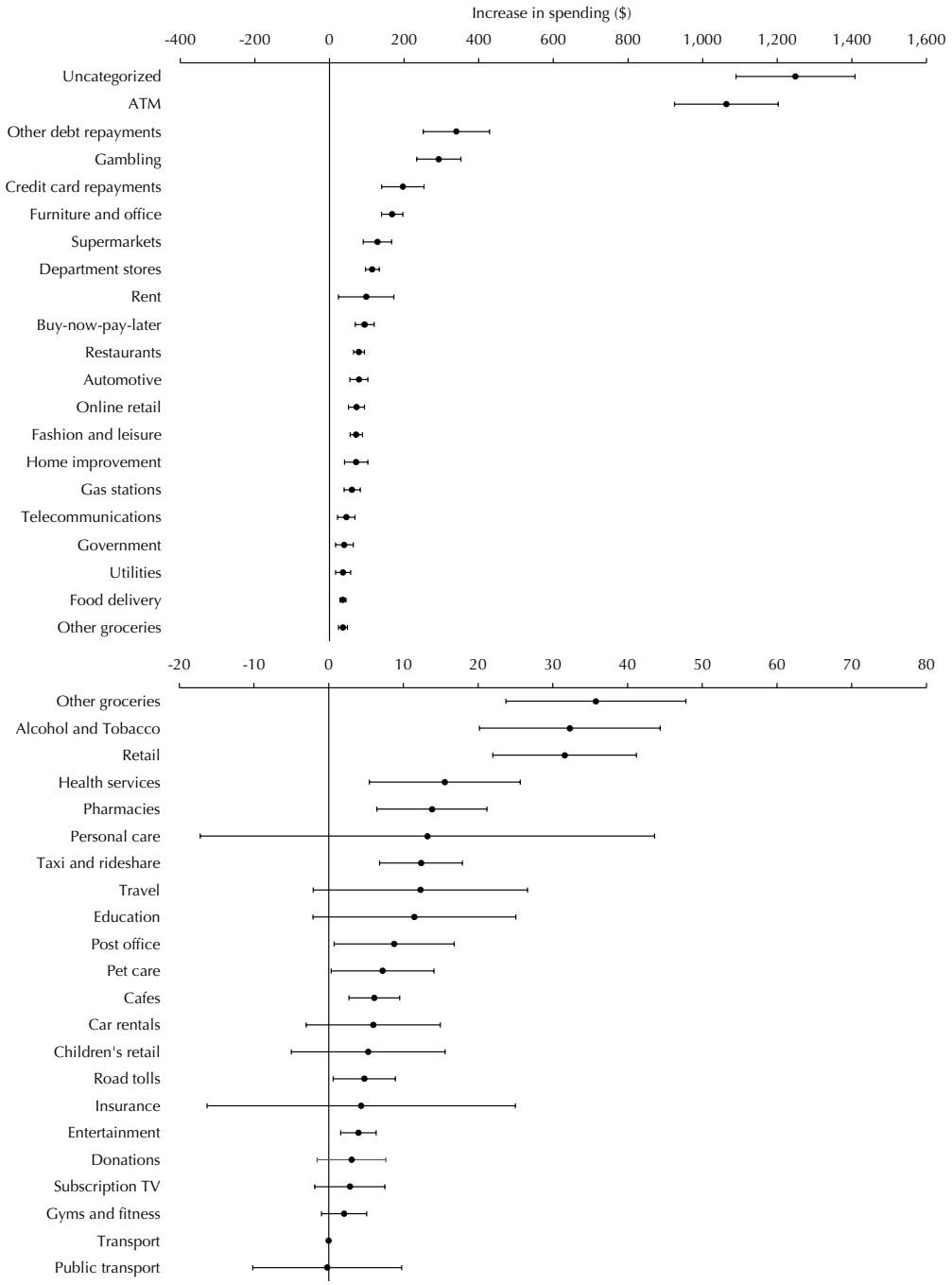
All other categories had spending impacts below $400, or less than 5% of the total. Spending was notably dispersed: of the 40 other discernible categories, 26 had spending impacts statistically significant at the 99% level, three at the 95% level, two at the 90% level, and only nine (personal care, car rentals, children's retail, insurance, donations, subscription TV, gyms and fitness, transport, and public transport) not statistically significant at the 90% level. Gambling was the third-largest discernible category (larger than credit card repayments).

We cannot distinguish perfectly between durables and non-durables,[53] but many of the spending categories that had highly statistically significant spending impacts are clearly non-durables (e.g., food delivery and supermarkets); overall, categories that are clearly non-durables sum to 60% of the spending impact across all discernible categories.[54] This is conservative as the other categories (e.g., retail) will also have included spending on non-durables. If we assume the same share of non-durables spending within uncategorized and ATM withdrawals, then our estimates imply a lower bound on the marginal propensity to consume (MPC) out of the first withdrawal of 0.26 (0.29 for the second withdrawal).

[53]The US Department of Commerce defines durables as those lasting three years or more.

[54]Clearly non-durable categories include gambling, supermarkets, rent, restaurants, gas stations, government, utilities, food delivery, other groceries, alcohol and tobacco, health services, pharmacies, personal care, taxi and rideshare, travel, education, post office, pet care, cafes, car rentals, road tolls, insurance, entertainment, donations, subscription TV, gyms and fitness, transport, public transport, totalling $1,039.26 out of $1,720.82 in total discernible spending.

Figure 8: Estimated cumulative ATTs of the first withdrawal by category



Data: Illion

Notes: Results are based on cohort ATTs estimated via the R package 'fixest', which implements Sun and Abraham (2021). We compute weekly aggregate ATTs by averaging across cohorts weighted by cohort share. We then accumulate over the first eight post-treatment weeks. The 'did' and 'fixest' statistical packages do not generate standard error estimates for cumulative ATTs. Moreover, when summing coefficients across time, one requires the variance-covariance matrix from the estimation procedure, and this is only generated for the cohort regressions rather than the weighted average aggregate regressions. To derive analytically standard errors for our spending category cumulative aggregate ATT estimates, we take the variance-covariance matrix from the cohort regression and exploit the fact that: 1) $\text{Cov}\left(\sum_{i=1}^{m} a_i X_i, \sum_{j=1}^{n} b_j Y_j\right) = \sum_{i=1}^{m} \sum_{j=1}^{n} a_i b_j \text{Cov}\left(X_i, Y_j\right)$ and 2) $\text{SE}\left(X_i + X_j\right) = \sqrt{\text{Var}\left(X_i\right) + \text{Var}\left(X_j\right) + 2 \cdot \text{Cov}\left(X_i, X_j\right)}$. Confidence intervals are at the 95% level.

5 Heterogeneity

5.1 MPX distribution

Because our bank transactions dataset is a panel, we observe income and spending at the individual level before and after withdrawal, which allows us to estimate individual-level treatment effects. Specifically, for each treated unit we compute the difference in average spending between the three weeks before and the three weeks after withdrawal and then divide by the withdrawal amount (Figure 9b).[55,56] As is evident in Figure 9b, these estimates are subject to error. But because we observe a pre-period for both the withdrawers and non-withdrawers, we can remove two components of this error: the time-invariant component specific to the withdrawers and the time-varying component common to the withdrawers and non-withdrawers.

To isolate the time-invariant component, among the same individuals we repeat the exercise just described on a timeframe three weeks earlier, computing average spending in the three weeks before withdrawal, subtracting average spending in the three weeks before that, and then dividing by the withdrawal amount (Figure 9a). One can think of this as a 'placebo' MPX distribution, which—as expected—is simply random noise centered around zero. To isolate the time-varying component, we compute the same two estimates among those who do not withdraw, but scaled by the average withdrawal among the withdrawers.

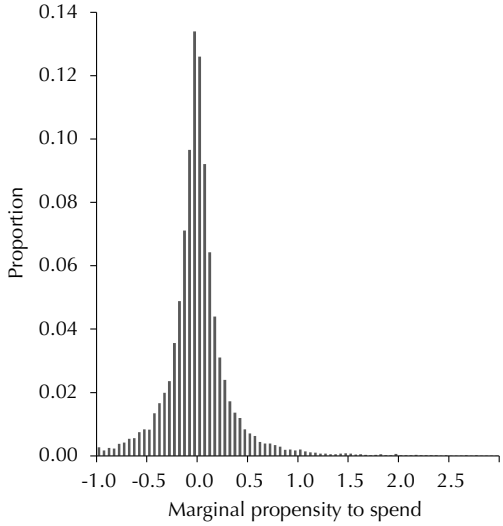
These scaled spending differences can serve as each of the four objects in a standard two-by-two differences-in-differences setup but applied to the quantiles of the MPX distribution rather than its mean (i.e., 'quantile difference-in-differences) (Athey and Imbens 20XX). The two differences strip out the time-invariant and time-varying errors in spending, isolating an estimate of the full distribution of the MPX. In Figure 9c, we display our MPX estimates by centile with 95% confidence intervals estimated via a standard bootstrap procedure. Each estimate represents the upper bound of MPXs for a given share of observations (e.g., half of the observations have an MPX of 0.51 or less).

This distribution has two striking features. First, the lowest 95% of MPXs is close to uniformly distributed (the dashed line indicates estimates under a uniform distribution). There is a little additional mass below the median and a little missing mass above, but otherwise the distribution is very close to uniform. Notably, this part of the distribution is neither bimodal (with excess mass at zero and one) nor strongly right-skewed (with excess

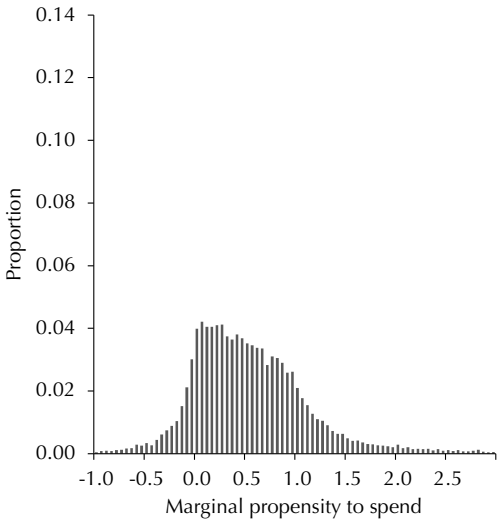
[55]This is similar to the approach taken by Karger and Rajan (2021) in studying the 2020 US stimulus program.

[56]Because the spending impact lasted eight weeks on average, this will underestimate the true treatment effect—though 83% of additional spending occurred in the first three weeks. Extending our individual-level estimates to eight weeks would require us to extend the pre-period, cutting the sample size and making it impossible to estimate a placebo-period distribution, given we observe each unit only for a 90-day window. Note that the average MPX implied by the mass in the unit interval is 0.435, compared to 0.431 in our main difference-in-differences procedure.

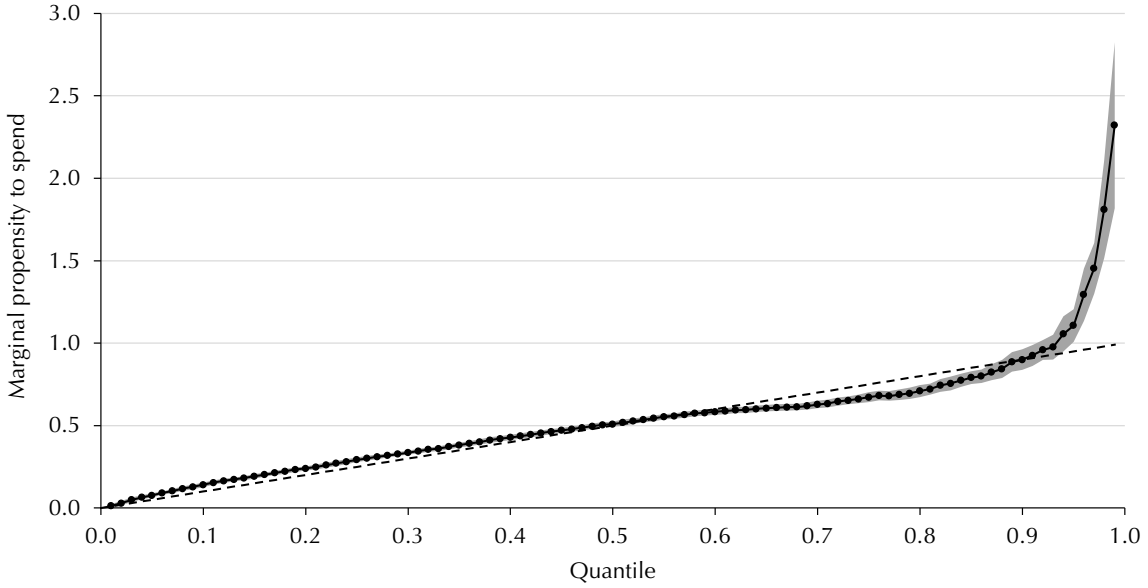
Figure 9: Estimated quantile treatment effects of withdrawal on spending among the treated



(a) Pre-treatment MPX distribution among treated



(b) Post-treatment MPX distribution among treated



(c) Quantile difference-in-differences of MPX

Data: Illion

Notes: Subfigures (a) and (b) display histograms (bin size 0.05) of individual-level MPX estimates via simple differences in spending across consecutive three-week periods among the withdrawers. Each unit's spending difference is divided by its eventual withdrawal amount to generate an individual-level MPX estimate. The treatment period (subfigure (b)) compares three weeks either side of withdrawal; the placebo period (subfigure (a)) compares three weeks prior to treatment and the three weeks prior to that. Subfigure (c) displays quantile difference-in-differences (qdid) estimates (by centile) with 95% confidence intervals estimated via bootstrap. The qdid estimates are constructed by computing the difference in the individual-level MPX at each quantile between the post-treatment period (subfigure (b)) and pre-treatment period (subfigure (a)) among those who withdrew, and subtracting the corresponding differences among those who did not withdraw. An MPX of 0.5 at a quantile of 0.5 indicates that the median of the individual-level MPX distribution rose 0.5 units more among those who withdrew than among those who did not. The dashed line indicates estimates under a uniform distribution.

mass concentrated at zero). This uniformity is also present in the density estimated by Karger and Rajan (2021)) for the US pandemic stimulus, in which US$1,000 checks were distributed broadly, though that density had a large spike at zero.

Second, the distribution has a long right tail, with 5% of observations exhibiting an MPX substantially above one (the top 1% have an MPX of at least 2.3). This is consistent with this fraction of withdrawers being subject to a spending friction that was relieved by the program. It may be the case that these withdrawers wished to purchase a high-value item for which they could not secure sufficient financing, and the withdrawal allowed them to bridge that financing gap.

5.2 MPX predictors

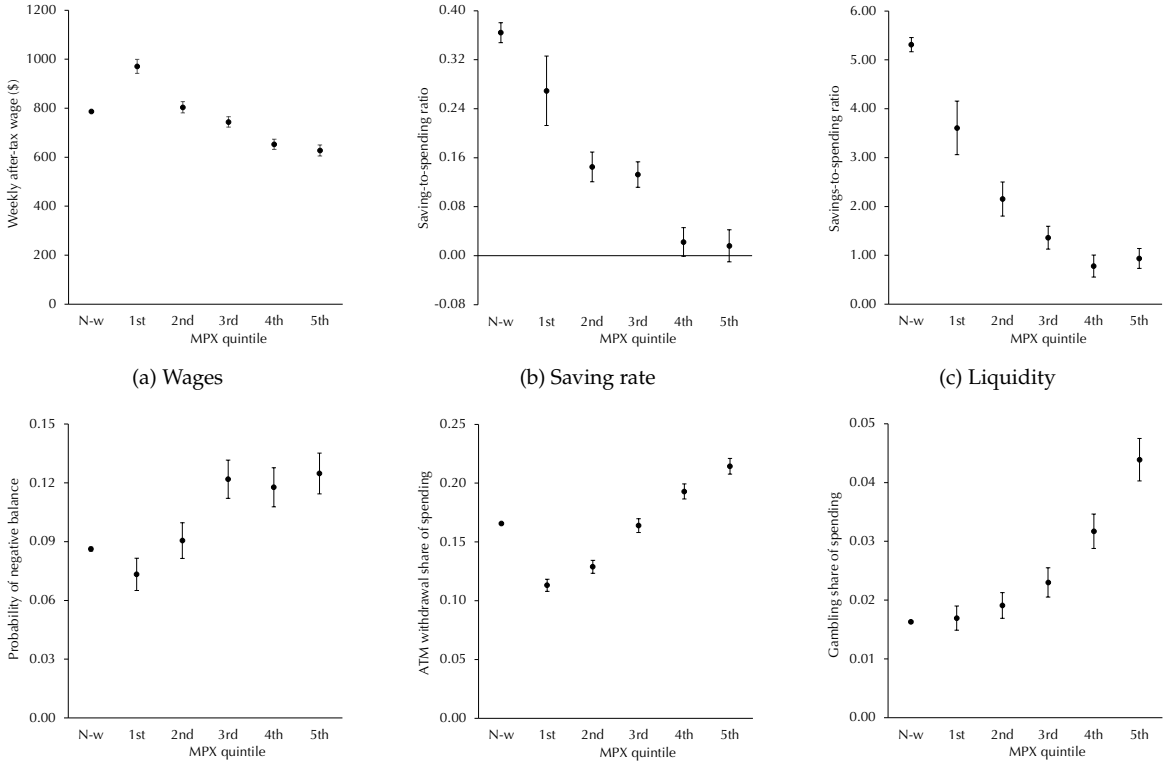
Earlier, we found that withdrawers had substantially worse financial health prior to withdrawal; now, we investigate how that covaries among withdrawers with their propensity to spend. In Figure 10, having split the withdrawer sample into quintiles of the individual-level MPX estimate, we display estimated means of pre-treatment variables for each quintile. Given the near-uniformity of the MPX distribution and the random noise introduced by fluctuations in spending, the conversion to quantiles is an approximate normalization of MPXs to the unit interval. As a reference point, we present on the left the corresponding estimated mean among those who did not withdraw (a group five times larger than the withdrawers).

All of the pre-treatment variable mean estimates differ with the estimated MPX in the expected directions: poorer pre-treatment financial health strongly predicts greater spending, consistent with the existing literature on substantially smaller transfers (Johnson et al., 2006; Broda and Parker, 2014; Kreiner et al., 2019). Wages varied across the MPX distribution, falling 35% between the first and fifth quintiles, with half this decline between the first two quintiles. The variation in financial health was far more dramatic. Between the first and second MPX quintiles, the saving rate halved and liquidity nearly halved. The 40% with MPXs exceeding 0.63 (around $6,000 of additional spending over eight weeks after the first round alone) were saving nothing and had savings at or below monthly spending. Even the 40% with MPXs between 0.09 and 0.63 had savings to cover no more than an additional month of spending, saving less than 15% of outlays. The 60% with MPXs of 0.34 or more were nearly twice as likely to have an overdrawn account than the 20% with MPXs of 0.09 or less.

We also identify two pre-treatment spending categories that were strongly related to the MPX: ATM withdrawals and gambling. As noted earlier, Australia is predominantly a cashless society, at least in formal markets. And gambling is more lightly regulated than in the US (online betting is legal, for example), with higher average losses.[57] Recall these two categories were the largest and third-largest discernible uses of withdrawn funds.

[57] https://www.nytimes.com/2018/04/04/world/australia/australians-gambling-betting-machines.html

Figure 10: Estimated pre-treatment variable means by estimated MPX quintile vs non-withdrawers



(a) Wages (b) Saving rate (c) Liquidity

(d) Overdrawn account (e) Cash withdrawals (f) Gambling

Data: Illion

Notes: Non-withdrawers on the left; recall they are roughly five times the withdrawers in number. Withdrawers are divided into quintiles based on the following MPXs: (-0.56, 0.09], (0.09, 0.34], (0.34, 0.63], (0.63, 0.97], (0.97, 2.7]. The 4% of withdrawers with MPXs outside this range are omitted. Outcomes are averages during the month prior to withdrawal. 95% confidence intervals shown.

Among those with higher MPXs, both pre-treatment ATM withdrawals and gambling were substantially higher, but rates of gambling increased at an increasing rate—between the lowest and highest spenders, the rate of pre-treatment gambling more than doubled.

Comparing to the non-withdrawers is informative. There was a modest difference in wages between the withdrawers and non-withdrawers, but low spenders had higher wages than the non-withdrawers and high spenders had lower wages. This same pattern applied to cash withdrawals. Contrast this with the saving rate, liquidity, and gambling: for all three, the average for every MPX quintile was lower (higher in the case of gambling) than the average among the non-withdrawers. It was a similar story with the probability of being overdrawn, with all but the lowest MPX quintile having a higher probability than the non-withdrawers.

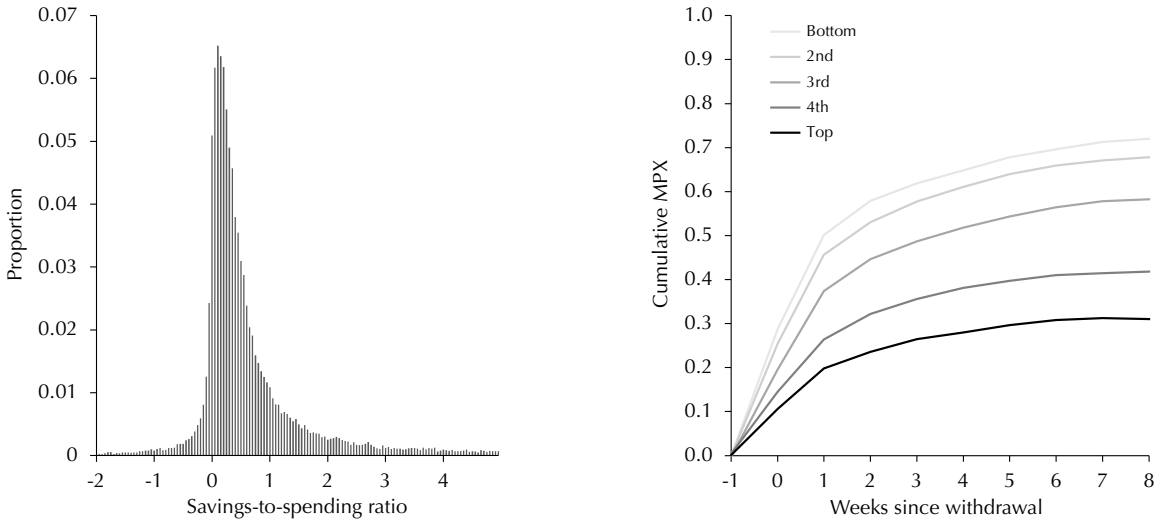
While there was variation among the withdrawers, they appear clearly divisible: roughly 20% had MPXs below 0.09 and financial health that was not too dissimilar from the non-withdrawers; the remaining roughly 80% had MPXs above 0.09 and sharply worse financial health than the non-withdrawers. Various measures decline rapidly with the MPX and then plateau. The top 40–60% of spenders were strongly homoegeneous, being statistically indistinguishable along multiple measures.

5.3 Liquidity

To assess the relationship between financial health and the MPX with greater precision, we focus on the ratio of savings to spending (a measure of liquidity) just prior to withdrawal. In Figure 11a, we present the estimated density of liquidity among the withdrawers, the average of which (2.07) was substantially lower than that among the non-withdrawers (5.38). We then divide the liquidity distribution into quintiles and estimate our main difference-in-differences regression separately for each quintile. We then accumulate the resulting weekly spending impacts following withdrawal and divide by the average withdrawal amount in each quintile.

The results are displayed in Figure 11b, and indicate a substantial and monotonic increase in the MPX, for every week post-treatment, as liquidity declines. The MPX among the bottom two liquidity quintiles is similar, with the least-liquid 40% having an MPX (0.68–0.72) more than double that among the most liquid 20% (0.31). This translates to additional spending of around $2,500 over eight weeks—equivalent to almost an entire month's post-tax wages for the former group.

Figure 11: The relationship between liquidity and spending



(a) Liquidity histogram

(b) Spending by liquidity quintile

Data: Illion
Notes: Liquidity is savings divided by spending on average during the month prior to withdrawal. For each liquidity quintile, we estimate cohort ATTs via the R package, 'did', which implements Callaway and Sant'Anna (2021). We compute weekly aggregate ATTs by averaging across cohorts weighted by cohort share. We then accumulate these by week and divide by the average withdrawal amount in the relevant liquidity quintile.

6 Interpretation

6.1 Two-asset Heterogeneous Agent Model

In this section, we develop a theoretical framework and use it to interpret quantitatively the evidence presented in the previous sections.[58] The framework has the following ingredients: i) incomplete markets (partial equilibrium), income risk, and borrowing constraints (Huggett, 1993); ii) two assets, a liquid asset and an illiquid asset that is costly to adjust (Kaplan and Violante, 2014); and iii) the potential for naively present-biased households (Laibson et al., 2021). We focus on non-durables consumption as durables are difficult to discern in our data, and the non-durables MPX is closer to the theoretical concept of the MPC (Laibson et al., 2022). Finally, we calibrate the model for the sub-population of withdrawers.[59]

[58]This evidence clearly demonstrates that withdrawers were, on average, younger households with low liquid asset holdings. Moreover, withdrawers did not adjust their consumption at all in anticipation of the withdrawal and a large fraction did not withdraw right away. Put together, these facts suggest liquidity constraints (Agarwal and Qian, 2014) and present-biased behavior (Andersen, 2020) are natural candidates to rationalize the large monthly spending responses we observe.

[59]There are two potential alternatives to the liquidity constraints present-biased model we use. First, we could have used the model in Beraja and Zorzi (2023) in which durables consumption is lumpy and the MPC does not decrease substantially with the amount of the liquidity injection. However, in our case, a large spending response is driven by non-durables alone. Second, we could have used the expenditure shocks model in Miranda-Pinto,

As in Kaplan et al. (2018), time is continuous and households maximize the present discounted value of utility:

$$\max_{\{c_t, d_t\}} \mathbb{E}_0 \int_0^\infty e^{\rho t} u(c_t) dt, \tag{1}$$

subject to:

$$\begin{aligned}
\dot{b}_t &= (1-\xi) w_t z_t + \left(r^b + \phi \cdot \mathbf{1}(b<0)\right) b_t - d_t - \chi(d_t, a_t) - c_t \\
\dot{a}_t &= r^a a_t + \xi w_t z_t + d_t \\
a_t &\geqslant 0 \\
b_t &\geqslant \underline{b} \\
\chi(d,a) &= -\chi_0 \cdot \min\{d,0\} + \frac{\chi_1}{2}\left(\frac{\min\{d,0\}}{a}\right)^2 a + \chi_2 \cdot \max\{d,0\} + \frac{\chi_3}{2}\left(\frac{\max\{d,0\}}{a}\right)^2 a,
\end{aligned}$$

with productivity z_t following a stochastic process (Poisson). Consumption is c_t, liquid asset holding is b_t, illiquid asset holding is a_t, wage income is w, liquid asset deposit/withdrawal is d_t, the risk-free interest rate on deposits of the liquid asset is r^b, the wedge on liquid asset borrowing ($b < 0$) is ϕ, and the risk-free return on the illiquid asset is r^a. A fraction ξ of labor income (pension saving), is deposited into the illiquid account at no cost. The borrowing limit is $\underline{b}$ and the asymmetric cost of (voluntarily) adjusting the illiquid asset holdings is $\chi(d, a)$. Households discount the future at rate ρ, which we adjust by a death rate ζ given an average lifespan of 45 years (540 months).

Following Laibson et al. (2021), we also accommodate present-biased households featuring instantaneous-gratification time preferences (quasi-hyperbolic discounting), with a naive perception that their future selves will behave as rational households. In particular, for these households, we assume the following instantaneous gratification discounting function:

$$D(t) = \begin{cases} 1 & \text{if } t = 0 \\ \beta e^{-\rho t} & \text{if } t > 0 \end{cases}. \tag{2}$$

When $\beta = 1$, we recover the exponential discounting in Equation (1). As demonstrated by Laibson et al. (2021), the consumption policy rules for CRRA preferences are:

- for all $b > \underline{b}$, $c(x) = \beta^{-\frac{1}{\gamma}} \hat{c}(x)$

Murphy, Walsh and Young (2023). In their model, non-durables consumption could display a large spike at the time of the liquidity shock for households that are liquidity constrained but also unable to cover expenditure shocks they experienced before withdrawal. We do not pursue this modeling approach for two reasons. First, these households have large utility gains when covering these expenses, which is inconsistent with the fact that a large fraction of households did not withdraw within the first two weeks of the policy but waited several weeks, even when the cost of applying for withdrawal was relatively small. Second, the largest discernible spending category was gambling, which cannot be considered an expenditure shock.

- for $b = \underline{b}$, $c(x) = \min\left\{\beta^{-\frac{1}{\gamma}}\hat{c}(x), (1-\xi)y + r\underline{b}\right\}$,

in which $\hat{c}(x)$ is the consumption policy function that the naive household considers it will adopt in the future. The model in Laibson et al. (2021) has several different implications from models with impatient households. For instance, the portfolio choice of a present-biased household is more akin to that of a patient household. Intuitively, for a present-biased household, consumption decisions are *small* decisions on a flow variable, while illiquid assets' adjustments are lumpy and *large* decisions on a stock variable.

6.2 Calibration

In Table 6, we report the externally calibrated parameters in our model. We set the monthly interest rate on illiquid assets using the observed returns on Australian pension savings. The median return (net of fees and taxes) on Australian pension savings for the last 29 years is 8.3%, which implies an annual real return, net of average inflation (2.58%), of 5.72% (0.47% per month). The real return on liquid wealth (2% per year) is from Kaplan et al. (2018). The monthly wedge on borrowing ϕ is 0.75%, which we obtain from the 14.18% interest on unsecured personal loans from the Reserve Bank of Australia, net of average inflation. The income process follows Achdou, Han, Lasry, Lions and Moll (2022), adapted to a monthly frequency. We discretize an AR(1) process, with annual persistence $\rho_z = 0.9$ and standard deviation $\sigma_z = 0.2$ (Guvenen, Kambourov, Kuruscu, Ocampo and Chen, 2023), into a monthly two-state Poisson process with incomes states $z_1 = 0.94$ and $z_2 = 1.06$, and a jump probability of 0.88. The borrowing limit $\underline{b}$ is one-third of monthly wages ($-w/3$), which corresponds to around a A$2,000 credit card limit.

Our internal calibration entails finding the discount rate ρ and/or the present-bias parameter β that matches the average MPC in the data. We obtain the average MPC out of pension withdrawals by multiplying the average MPX by our lower bound on the share of non-durables in the spending response, which is 60%. Hence, our target is an average MPC of 0.31. We calculate the model's implied average MPC out of a two-wage windfall, as the first or second withdrawal.

In Table 7, we report the moments from three versions of the model. In column 2, we show the model-implied moments of a standard exponential calibration in which we assume $\rho = 0.4\%$, which is equivalent to a monthly subjective discount factor of $1/(1+0.4\%+\zeta) = 0.994$ and an annual discount factor of 0.93, as in Kaplan et al. (2018). This calibration delivers an average MPC, out of a two-wage windfall, of 2.9%, which is an order of magnitude smaller than that observed in the data. In column 3, we allow the discount rate ρ to vary so as to match the observed average MPC. The implied calibrated discount rate is 17%, which is equivalent to an annual discount factor of 0.15, substantially below calibrated values in the

Table 6: Externally calibrated parameters

Parameter	Description	Value	Source/Target
Preferences			
γ	Risk aversion	2	Standard
ζ	Death rate	$1/(45 \times 12)$	Avg. lifespan of 45 years
Assets			
$\underline{b}$	Borrowing limit	$-w/3$	Basic credit card limit Australia
ϖ	Interest rate wedge	0.75%	Reserve Bank of Australia
r^b	Liquid asset return	0.17%	Kaplan et al. (2018)
r^a	Illiquid asset return	0.47%	Australian Super
ξ	Share of income automatically deposited	10.5%	Australian regulation
χ_0	Adj. cost linear component withdrawals	1.1	Arbitrarily large (policy)
χ_1	Adj. cost convex component withdrawals	12	Arbitrarily large (policy)
χ_2	Adj. cost linear component deposits	0.002	Arbitrarily small (policy)
χ_3	Adj. cost convex component deposits	0.01	Arbitrarily small (policy)
Income process			
z_1, z_2	Income states	0.94, 1.06	Guvenen et al. (2023)
λ_1, λ_2	Income jumps	0.887	Guvenen et al. (2023)

literature.[60] In the final column of Table 7, we report our naively present-biased calibration. Given a standard value of $\rho = 0.4\%$, the calibrated value of the present-bias parameter β is 0.58, which lies between the values obtained by Ganong and Noel (2019) ($\beta \in [0.5, 0.9]$) and Gerard and Naritomi (2021) ($\beta = 0.44$).

In the final two rows of Table 7, we report additional moments that shed light on the key differences between the models. First, the three models have very different implications for liquid asset holdings. While the standard exponential model delivers an excessive liquid-savings-to-income ratio (319%), the model with high impatience delivers too little savings (1.9%). The present-biased model has an average ratio of liquid assets to income of 51.9% which is indeed close to the one observed in the data.[61] In the final row, we report the share of households at the borrowing limit. The model displays 10.2%, 94.4%, and 92.3% of households at the borrowing limit in the exponential benchmark model, the impatient version of the model, and the present-biased model, respectively.

[60] For instance, Aguiar, Bils and Boar (2020) calibrate a model with heterogeneous discount factors, and their lowest calibrated (annual) value for the discount factor is 0.72.

[61] We do not explicitly target the liquid asset holdings as in our data we do not have information on the stock of debt (only flow debt payments) or the stock of additional liquid savings (we only have information on checking and savings accounts).

Table 7: Calibration results

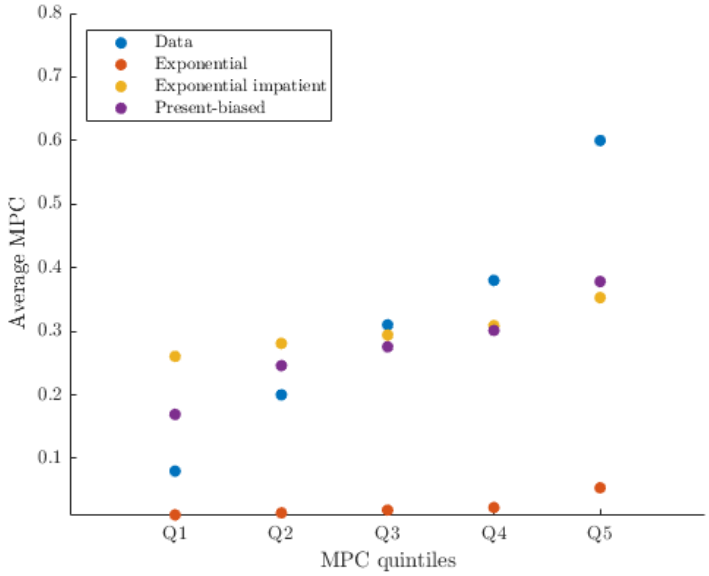
Parameter	(1) Data	(2) Exponential benchmark	(3) Exponential impatient	(4) Present-biased
Preferences				
ρ	-	0.4%	17%	0.4%
β	-	1	1	0.58
Calibration target				
Average MPC (two-wages windfall)	31%	2.9%	31.2%	31.3%
Additional moments				
Liquid assets to income	-	319%	1.9%	51.9%
Share of $b = \underline{b}$	-	10.2%	94.4%	92.3%

6.3 MPC heterogeneity

Next we study the fit of the models in terms of MPC heterogeneity and the empirical relationship between liquidity and spending responses. In Figure 12, we display the average MPC by MPC quantile for each of the three models. One can see that the exponential benchmark delivers very limited heterogeneity in consumption responses. Even the top quintile, mainly composed by liquidity constrained households, displays a small average MPC of 5.3%. On the other hand, while the model with extremely impatient households is able to match the average MPC (Table 7), it fails to delivers significant MPC heterogeneity. The present-biased model provides the best fit to the data.

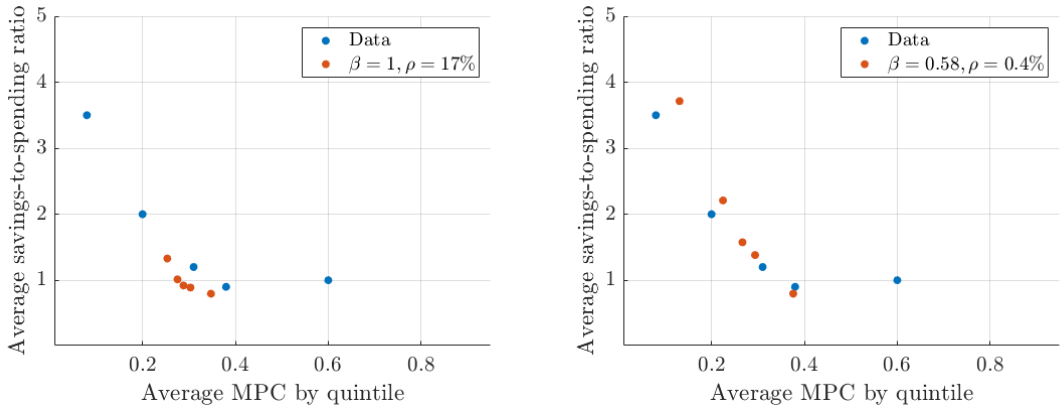
We now investigate the model implied relationship between liquidity and MPC, across MPC quantiles. In the left and right panels of Figure 13, we display results for the exponential impatient and present-biased models, respectively. It is apparent that the model with impatient households not only misses the MPC heterogeneity but also fails to match the heterogeneity in liquid asset holdings. On the other hand, the model with present-biased households is very close to replicating the observed relationship between liquidity and MPC. The one exception is the very highest MPC quintile, in which the observed MPC is 0.6 but the model can only deliver an MPC of 0.38. In evaluating the strongly right-skewed MPX distribution in Section 5, we posited that the top 5% having MPXs significantly exceeding 1 may be due to lumpy expenditures in the present of liquidity constraints. Since our model does not include this feature, this lack of fit is unsurprising.

Figure 12: Average MPC across quintiles



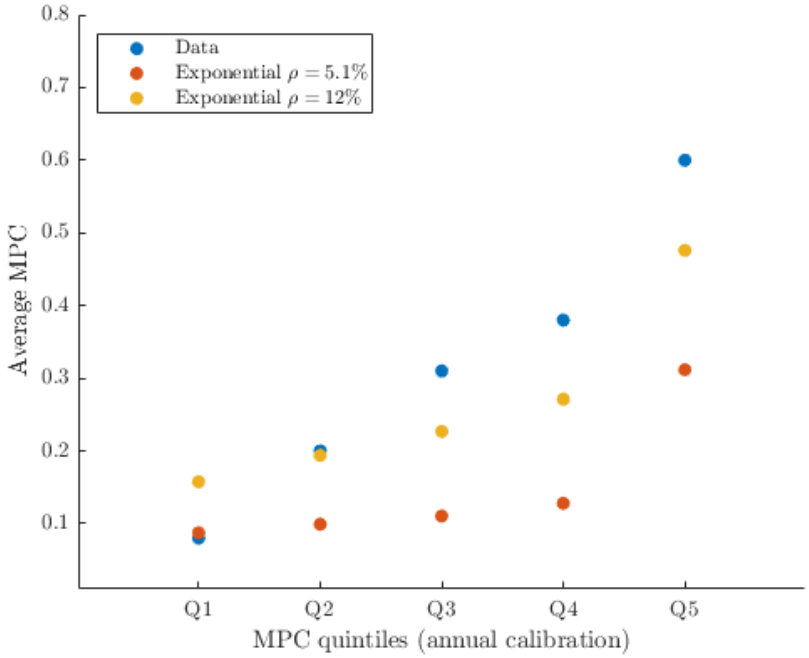
Notes: The y-axis reports the average MPC for the corresponding MPC quintiles in the x-axis. To obtain the average MPC we use the wights from the stationary distribution of assets.

Figure 13: Liquidity and average MPC across quintiles



Notes: Savings to spending in the model is $(b + w)/c$, which compares to the empirical counterpart. The y-axis reports average liquidity for MPC quintiles. The average MPC is the weighted average MPC, using the stationary distribution of assets, of the respective quintile. The figure on the left shows the model with impatient households and the figure on the right shows the model with present-biased naive households.

Figure 14: Average MPC across quintiles in annual calibration



Notes: The y-axis reports the average MPC for the corresponding MPC quintiles in the x-axis. To obtain the average MPC we use the wights from the stationary distribution of assets.

6.4 Importance of high-frequency data

A key insight of the calibration exercise is the importance of high-frequency (at least monthly) data. To draw this out, we ignore the high-frequency spending patterns and calibrate our model with aggregated annualized data. We thus consider both withdrawals, which for the modal withdrawer represented A$20,000 (about half annual wages). In Figure 14, we report the average MPC across the MPC distribution. We plot the results for a standard discount factor value (0.93 annual) and for a value that matches the average MPC (0.31) in the data (0.87 annual). At the annual frequency, a two-asset heterogeneous agent model with borrowing constraints is able to explain the observed consumption patterns.

However, such a calibration is misleading, for a few reasons. First, the majority of the spending increase occurred within just the first two weeks after withdrawal. Thus, a calibration that targets the annual MPC implicitly imposes a counterfactually "smoother" spending impulse. Second, at the annual frequency, the relative size of the liquidity injection is four times smaller than at the monthly frequency. While the two pension withdrawals represent a liquidity injection of half average annual income, the first (or second) withdrawal represents more than two months of income. This is an important consideration as the spending responses in the models considered here decrease considerably with the size of the

transfer. Third, the discount factor at the annual frequency is significantly smaller than the discount factor at the monthly frequency, implying a higher degree of impatience.

7 Concluding comments

We contribute to a recent and active literature generating empirical evidence in favor of a behavioral explanation for the sensitivity of consumption to fiscal transfers. Parker (2017) presents survey evidence on the 2008 US stimulus checks, the consumption response to which is predictable based on income several years prior, and is associated with sophistication and planning, and impatience. Ganong and Noel (2019) study the predictable exhaustion of unemployment insurance (UI) in the US, observing a lack of the anticipation we would expect among rational, forward-looking (but liquidity-constrained) people. Their evidence suggests there is variation in the degree of present bias across recipients, consistent with our finding of a broadly distributed MPX. And Ganong, Greig, Noel, Sullivan and Vavra (2022) find the supplementary pandemic UI payments in the US raised consumption substantially, consistent with our finding of consumption rising by 136% over the first two weeks.

Something we do not do is detail exactly what it is about the recipients as people that led them to engage in time-inconsistent behavior. Our evidence on pre-treatment ATM withdrawals and gambling, and age was striking—based on the literature in clinical psychology, this suggests a link between impulsivity and the MPX.[62] The survey evidence of Parker (2017), that the consumption response is associated with sophistication and planning, and impatience, seems consistent with this, and points to a role for better financial literacy (Lusardi and Mitchell, 2014; van Rooji, Lusardi and Alessie, 2012). Moreover, our settling highlights that even the 83% who did not participate, many of who we might otherwise think of as rational and forward-looking, were evidently subject to behavioral frictions, perhaps in the form of the commitment device proposed by Attanasio et al. (2020). Overall, deeper investigation of the mechanisms behind the behavioral types' responses to fiscal transfers is needed.

The Super withdrawal program serves as a cautionary tale for the design of private retirement saving systems, which have gained renewed interest as the US Social Security trust funds near depletion.[63] The US 401(k) system is unique globally in its high degree of liquidity (Beshears et al., 2015), loosened even further during the pandemic, with Vanguard reporting early withdrawals reached 2.8% in 2022, compared to a pre-pandemic average of 2%.[64] Under

[62]Maclaren, Fugelsang, Harrigan and Dixon (2011) conduct a meta-analysis of 44 studies in clinical psychology, noting a link between urgency or impulsivity and gambling. Canale, Vieno, Griffiths, Rubaltelli and Santinello (2015) use experimental and survey evidence to establish a link between age, urgency, and gambling.

[63]https://thehill.com/policy/finance/3843718-pence-weve-got-to-have-a-conversation-about-reforming-social-security/

[64]https://www.wsj.com/articles/short-on-cash-more-americans-tap-401-k-savings-for-emergencies-

the Super withdrawal program, the vast majority of people who were eligible chose not to access their retirement savings when given a seemingly one-off opportunity to do so, and the vast majority of those who did appeared to be driven by present bias. Accordingly, as a matter of retirement saving policy, it is difficult not to view illiquidity as welfare-improving in aggregate—consistent with its ubiquity in retirement saving systems outside the US (Fadlon and Laibson, 2022).

As macro-stabilization policy, the welfare impact is not so clear cut. To the extent it overcame fiscal constraints, it improved macro-stability, increasing welfare—including among the withdrawers. The present-biased will pay in sub-optimal future consumption—but this is also true of cash stimulus, which can be saved rather than spent. The question is whether macro-stability is funded by the lower future retirement incomes of the few or higher future taxes on the many, the consequences of which depend on the tax and transfer system. To the extent withdrawers are net-beneficiaries of that system, they may have been relatively worse off under the program.

By connecting directly the individual-level costs and benefits of using cash transfers to stabilize the economy—as opposed to an indirect connection via higher future taxes under traditional cash stimulus—the Super withdrawal program also highlights a perversity of cash stimulus generally. The greater the present bias, the more effective is cash stimulus (Laibson et al., 2021). But, by definition, those induced to spend are making themselves worse off, at least directly, by doing so—and others better off (Auclert, Rognlie and Straub, 2023). Their error will be felt when eventually they have to pay the taxes necessary to fund that macro-stability. How this all nets out depends on the distributional properties of the tax and transfer system. The application of a comprehensive welfare frame to stimulus under present bias could provide a valuable guide to policy (Maxted, 2022). Channelling Tobin (1977): just how many Harberger triangles does it take to fill an Okun's gap?

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References

Achdou, Y., Han, J., Lasry, J.-M., Lions, P.-L. and Moll, B. (2022), 'Income and wealth distribution in macroeconomics: A continuous-time approach', *The Review of Economic Studies* **89**(1), 45–86.

Agarwal, S. and Qian, W. (2014), 'Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in Singapore', *American Economic Review* **104**(12), 4,205–4,230.

Aguiar, M. A., Bils, M. and Boar, C. (2020), 'Who are the hand-to-mouth?'. *NBER Working Papers*, available here: `https://www.nber.org/system/files/working_papers/w26643/w26643.pdf`.

Aladangady, A., Aron-Dine, S., Cashin, D., Dunn, W., Feiveson, L., Lengermann, P., Richard, K. and Sahm, C. (2023), 'Spending responses to high-frequency shifts in payment timing: Evidence from the Earned Iincome Tax Credit', *American Economic Journal: Economic Policy* **15**(3), 89–114.

Andersen, K. Y. (2020), 'Spending when illiquid savings become liquid: Evidence from Danish wage earners'. Available here: `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3696220`.

Angeletos, G.-M., Laibson, D., Repetto, A., Tobacman, J. and Weinberg, S. (2001), 'The hyperbolic consumption model: Calibration, simulation, and empirical evaluation', *Journal of Economic Perspectives* **15**(3), 47–68.

Argento, R., Bryant, V. L. and Sabelhaus, J. (2014), 'Early withdrawals from retirement accounts during the Great Recession', *Contemporary Economic Policy* **33**(1), 1–16.

Ashraf, N., Karlan, D. and Yin, W. (2006), 'Tying Odysseus to the mast: Evidence from a commitment savings product in the Philippines', *The Quarterly Journal of Economics* **121**(2), 635–672.

Attanasio, O., Kovacs, A. and Moran, P. (2020), 'Temptation and commitment: Understanding hand-to-mouth behavior'. *NBER Working Papers*, available here: `https://www.nber.org/system/files/working_papers/w27944/w27944.pdf`.

Auclert, A., Rognlie, M. and Straub, L. (2023), 'The trickling up of excess savings'. *NBER Working Papers*, available here: `https://www.nber.org/system/files/working_papers/w30900/w30900.pdf`.

Baker, S. R., Farrokhnia, A., Meyer, S., Pagel, M. and Yannelis, C. (2020*a*), 'How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic', *Review of Asset Pricing Studies* **10**(4), 834–862.

Baker, S. R., Farrokhnia, A., Meyer, S., Pagel, M. and Yannelis, C. (2020*b*), 'Income, liquidity, and the consumption response to the 2020 economic stimulus payments'. Conditionally accepted, *Review of Finance*, available here: `https://www.nber.org/papers/w27097`.

Barro, R. J. (1974), 'Are government bonds net worth?', *Journal of Political Economy* **82**(6), 1,095–1,117.

Beraja, M. and Zorzi, N. (2023), 'On the size of stimulus checks: How much is too much?'. Available here: https://conference.nber.org/conf_papers/f184287.pdf.

Beshears, J., Choi, J. J., Harris, C., Laibson, D., Madrian, B. C. and Sakong, J. (2020), 'Which early withdrawal penalty attracts the most deposits to a commitment savings account?', *Journal of Public Economics* **183**, 104–144.

Beshears, J., Choi, J. J., Hurwitz, J., Laibson, D. and Madrian, B. C. (2015), 'Liquidity in retirement savings systems: An international comparison', *American Economic Review: Papers and Proceedings* **105**(5), 420–425.

Besley, T. and Smart, M. (2007), 'Fiscal restraints and voter welfare', *Journal of Public Economics* **91**, 755–773.

Bishop, J. and Day, I. (2020), 'How many jobs did JobKeeper keep?', Discussion Paper 2020-07, Reserve Bank of Australia. Available here: https://www.rba.gov.au/publications/rdp/2020/2020-07.html.

Borusyak, K., Jaravel, X. and Spiess, J. (2022), 'Revisiting event study designs: Robust and efficient estimation'. Available here: https://arxiv.org/pdf/2108.12419.pdf.

Breunig, R. and Sainsbury, T. (2023), 'Too much of a good thing? australian cash transfer replacement rates during the pandemic.', *The Australian Economic Review* .

Broda, C. and Parker, J. A. (2014), 'The economic stimulus payments of 2008 and the aggregate demand for consumption', *Journal of Monetary Economics* **68**(S), S20–S36.

Callaway, B. and Sant'Anna, P. H. (2021), 'Difference-in-differences with multiple time periods', *Journal of Econometrics* **225**(2), 200–230.

Campbell, J. Y. and Mankiw, N. G. (1989), 'Consumption, income and interest rates', *NBER Macroeconomics Annual* **4**, 185–246.

Canale, N., Vieno, A., Griffiths, M. D., Rubaltelli, E. and Santinello, M. (2015), 'Trait urgency and gambling problems in young people by age: The mediating role of decision-making processes', *Addictive Behaviors* **46**, 39–44.

Carroll, C. D. (1997), 'Buffer-stock saving and the life cycle/permanent income hypothesis', *The Quarterly Journal of Economics* **112**(1), 1–55.

Chan, M. K., Morris, T., Polidano, C. and Vu, H. (2022), 'Income and saving responses to tax incentives for private retirement savings', *Journal of Public Economics* **206**.

Chetty, R., Friedman, J. N., Hendren, N. and The Opportunity Insights Team (2022), 'The economic impacts of COVID-19: Evidence from a new public database built using private sector data'. Available here: https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf.

Cohen, J., Ericson, K. M., Laibson, D. and White, J. M. (2020), 'Measuring time preferences', *Journal of Economic Literature* **58**(2), 299–347.

Coibion, O., Gorodnichenko, Y. and Weber, M. (2020), 'How did U.S. consumers use their stimulus payments?'. *NBER Working Papers*, available here: https://www.nber.org/system/files/working_papers/w27693/w27693.pdf.

Coyne, D., Fadlon, I. and Porzio, T. (2022), 'Measuring valuation of liquidity with penalized withdrawals'. *NBER Working Papers*, available here: https://www.nber.org/system/files/working_papers/w30007/w30007.pdf.

de Chaisemartin, C. and D'Haultfœuille, X. (2020), 'Two-way fixed effects estimators with heterogeneous treatment effects', *American Economic Review* **110**(9), 2,964–2,996.

Deaton, A. (1991), 'Saving and liquidity constraints', *Econometrica* **59**(5), 1,221–1,248.

Elias, M. (2022), 'Constructing real time estimates of Australian consumer spending using bank transactions'. Available here: https://e61.in/wp-content/uploads/2022/10/illion-data-ABS-retail-trade.pdf.

Fadlon, I. and Laibson, D. (2022), 'Paternalism and pseudo-rationality: An illustration based on retirement savings', *Journal of Public Economics* **216**.

Fagerang, A., Holm, M. B. and Natvik, G. J. (2021), 'MPC heterogeneity and household balance sheets', *American Economic Journal: Macroeconomics* **13**(4), 1–54.

Flynn, P. and Smith, T. (2022), 'Rivers, lakes and revenue streams: The heterogeneous effects of Clean Water Act grants on local spending', *Journal of Public Economics* **212**.

Friedman, M. (1957), *A Theory of the consumption function*, Princeton University Press, Princeton.

Ganong, P., Greig, F., Noel, P., Sullivan, D. M. and Vavra, J. (2022), 'Spending and job-finding impacts of expanded unemployment benefits: Evidence from administrative micro data'. Available here: https://bpb-us-w2.wpmucdn.com/voices.uchicago.edu/dist/1/801/files/2022/08/pandemic_ui.pdf.

Ganong, P. and Noel, P. (2019), 'Consumer spending during unemployment: Positive and normative implications', *American Economic Review* **109**(7), 2,383–2,424.

Garcia, R., Lusardi, A. and Ng, S. (1997), 'Excess sensitivity and asymmetries in consumption: An empirical investigation', *Journal of Money, Credit and Banking* **29**(2), 154–176.

Gelman, M. (2022), 'The self-constrained hand-to-mouth', *Review of Economics and Statistics* **104**(5), 1,096–1,109.

Gerard, F. and Naritomi, J. (2021), 'Job displacement insurance and (the lack of) consumption-smoothing', *American Economic Review* **111**(3), 899–942.

Goda, G. S., Jones, D. and Ramnath, S. (2022), 'Temporary and permanent effects of withdrawal penalties on retirement savings accounts', *Journal of Public Economics* **215**.

Goodman-Bacon, A. (2021), 'Difference-in-differences with variation in treatment timing', *Journal of Econometrics* **225**(2), 254–277.

Goodman, L., Mortensen, J., Mackie, K. and Schramm, H. R. (2021), 'Leakage from retirement savings accounts in the United States', *National Tax Journal* **74**(3), 689–719.

Guvenen, F., Kambourov, G., Kuruscu, B., Ocampo, S. and Chen, D. (2023), 'Use it or lose it: Efficiency and redistributional effects of wealth taxation', *The Quarterly Journal of Economics* **138**(2), 835–894.

Hamilton, S. (2020), 'A tale of two wage subsidies: The American and Australian fiscal responses to COVID-19', *National Tax Journal* **73**(3), 829–846.

Hsieh, C.-T. (2003), 'Do consumers react to anticipated income changes? Evidence from the Alaska Permanent Fund', *American Economic Review* **93**(1), 397–405.

Huggett, M. (1993), 'The risk-free rate in heterogeneous-agent incomplete-insurance economies', *Journal of Economic Dynamics and Control* **17**(5-6), 953–969.

Imbens, G. W., Rubin, D. B. and Sacerdote, B. I. (2001), 'Estimating the effect of unearned income on labor earnings, savings, and consumption: Evidence from a survey of lottery players', *American Economic Review* **91**(4), 778–794.

Johnson, D. S., Parker, J. A. and Souleles, N. S. (2006), 'Household expenditure and the income tax rebates of 2001', *American Economic Review* **96**(5), 1,589–1,610.

Kaplan, G., Moll, B. and Violante, G. L. (2018), 'Monetary policy according to HANK', *American Economic Review* **108**(3), 697–743.

Kaplan, G. and Violante, G. L. (2014), 'A model of the consumption response to fiscal stimulus payments', *Econometrica* **82**(4), 1,199–1,239.

Karger, E. and Rajan, A. (2021), 'Heterogeneity in the marginal propensity to consume: Evidence from COVID-19 stimulus payments'. Available here: `https://www.chicagofed.org/publications/working-papers/2020/2020-15`.

Kreiner, C. T., Lassen, D. D. and Leth-Petersen, S. (2019), 'Liquidity constraint tightness and consumer responses to fiscal stimulus policy', *American Economic Journal: Economic Policy* **11**(1), 351–379.

Kubota, S., Onishi, K. and Toyama, Y. (2021), 'Consumption responses to COVID-19 payments: Evidence from a natural experiment and bank account data', *Journal of Economic Behavior and Organization* **188**, 1–17.

Kueng, L. (2018), 'Excess sensitivity of high-income consumers', *The Quarterly Journal of Economics* **133**(4), 1,693–1,751.

Kuhn, P., Kooreman, P., Soetevent, A. and Kapteyn, A. (2011), 'The effects of lottery prizes on winners and their neighbours: Evidence from the Dutch postcode lottery', *American Economic Review* **101**(5), 2,226–2,247.

Laibson, D., Maxted, P. and Moll, B. (2021), 'Present bias amplifies the household balance-sheet channels of macroeconomic policy'. *NBER Working Papers*, available here: https://www.nber.org/system/files/working_papers/w29094/w29094.pdf.

Laibson, D., Maxted, P. and Moll, B. (2022), 'A simple mapping from MPCs to MPXs'. Available here: https://static1.squarespace.com/static/6186b3b155561c2ab5fe4957/t/62bbac0b4a72405ded5acaba/1656466443662/MPCMPX.pdf.

Leigh, A. (2012), 'How much did the 2009 Australian fiscal stimulus boost demand? Evidence from household spending effects', *The B.E. Journal of Macroeconomics* **12**(1).

Lusardi, A. and Mitchell, O. S. (2014), 'The economic implications of financial literacy: Theory and evidence', *Journal of Economic Literature* **52**(1), 5–44.

Maclaren, V. V., Fugelsang, J. A., Harrigan, K. A. and Dixon, M. J. (2011), 'The personality of pathological gamblers: A meta-analysis', *Clinical Psychology Review* **31**(6), 1,057–1,067.

Maxted, P. (2022), 'Present bias unconstrained: Consumption, welfare, and the present-bias dilemma'. Available here: https://static1.squarespace.com/static/6186b3b155561c2ab5fe4957/t/62e4a1a02af19807514b634e/1659150753483/Present+Bias+Unconstrained.pdf.

Mees, B. (2017), *Workers' capital: Industry funds and the fight for universal superannuation in Australia*, Allen & Unwin, Sydney.

Miranda-Pinto, J., Murphy, D., Walsh, K. J. and Young, E. R. (2023), 'A model of expenditure shocks'. Available here: https://cokeconphd.github.io/Website/ModelExpenditureShocks.pdf.

Nakamura, E. and Steinsson, J. (2014), 'Fiscal stimulus in a monetary union: Evidence from US regions', *American Economic Review* **104**(3), 753–792.

Nakamura, E. and Steinsson, J. (2018), 'Identification in macroeconomics', *Journal of Economic Perspectives* **32**(3), 59–86.

Orchard, J., Ramey, V. and Wieland, J. F. (2023), 'Micro MPCs and macro counterfactuals: The case of the 2008 rebates'. Available here: https://econweb.ucsd.edu/~vramey/research/Micro_MPCs_and_Macro_Counterfactuals.pdf.

Parker, J. A. (2017), 'Why don't households smooth consumption? Evidence from a $25 million experiment', *American Economic Journal: Macroeconomics* **9**(4), 153–183.

Parker, J. A., Soulless, N. S., Johnson, D. S. and McClelland, R. (2013), 'Consumer spending and the economic stimulus payments of 2008', *American Economic Review* **103**(6), 2,530–2,553.

Pfäuti, O., Seyrich, F. and Zinman, J. (2023), 'Heterogeneity in what? cognitive skills, beliefs and the liquid wealth distribution'. Available here: https://opfaeuti.github.io/website/PSZ.pdf.

Ramey, V. (2019), 'Ten years after the financial crisis: What have we learned from the renaissance in fiscal research', *Journal of Economic Perspectives* **33**(2), 89–114.

Ricardo, D. (1820), Funding system, *in* 'Supplement to the fourth, fifth, and sixth editions of the Encyclopædia Brittanica', Archibald Constable, Edinburgh.

Roth, J., Sant'Anna, P. H., Bilinski, A. and Poe, J. (2022), 'What's trending in difference-in-differences? A synthesis of the recent econometrics literature'. Conditionally accepted, *Journal of Econometrics*, available here: https://www.jonathandroth.com/assets/files/DiD_Review_Paper.pdf.

Sahm, C. R., Shapiro, M. D. and Slemrod, J. (2010), 'Household response to the 2008 tax rebate: Survey evidence and aggregate implications', *Tax Policy and the Economy* **24**(1), 69–110.

Sainsbury, T., Breunig, R. and Watson, T. (2022), 'COVID-19 private pension withdrawals and unemployment tenures'. *IZA Discussion Paper*, D.P. 15,399, Available here: https://www.iza.org/publications/dp/15399/covid-19-private-pension-withdrawals-and-unemployment-tenures.

Shapiro, M. D. and Slemrod, J. (2009), 'Did the 2008 tax rebates stimulate spending?', *American Economic Review* **99**(2), 374–379.

Song, M. H. and Song, S. (2023), 'Consumption response to anticipated income changes: Evidence from the magnitude effect'. Available here: https://nbviewer.org/github/melissahyunji/misc/blob/main/Melissa%20Hyunji%20Song_Job%20Market%20Paper.pdf.

Sun, L. and Abraham, S. (2021), 'Estimating dynamic treatment effects in event studies with heterogeneous treatment effects', *Journal of Econometrics* **225**(2), 175–199.

Tobin, J. (1977), 'How dead is Keynes?', *Economic Inquiry* **15**(4), 459–468.

van Rooji, M. C. J., Lusardi, A. and Alessie, R. J. M. (2012), 'Financial literacy, retirement planning, and household wealth', *The Economic Journal* **122**, 449–478.

Wang-Ly, N. and Newell, B. R. (2022), 'Allowing early access to retirement savings: Lessons from Australia', *Economic Analysis and Policy* **75**, 716–733.

Watson, T., Tervala, J. and Sainsbury, T. (2022), 'The JobKeeper payment: How good are wage subsidies?'. Available here: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4103865.

Wooldridge, J. M. (2022), 'Simple approaches to nonlinear difference-in-differences with panel data'. Available here: https://www.researchgate.net/profile/Jeffrey-Wooldridge/publication/362532821_Simple_Approaches_to_Nonlinear_Difference-in-Differences_with_Panel_Data/links/62eebd3b4532247693855929/Simple-Approaches-to-Nonlinear-Difference-in-Differences-with-Panel-Data.pdf.

Yannelis, C. and Amato, L. (2022), 'Household behavior (consumption, credit and investments) during the COVID-19 pandemic'. Forthcoming in *Annual Review of Financial Economics*, available here: https://faculty.chicagobooth.edu/-/media/faculty/constantine-yannelis/research/household-behavior.pdf.

Zeldes, S. P. (1989), 'Consumption and liquidity constraints: An empirical investigation', *Journal of Political Economy* **97**(2), 305–346.

Appendices

A Detailed description of the Super system

Australia has a compulsory, defined-contribution private retirement saving system, called 'superannuation'.[65] Under the system, all employers are required to contribute an additional 10.5% (rising to 12% by 2026) of the pre-tax wages (including bonuses but excluding overtime) of their employees to a private pension account.[66] The median balance by age in 2019 is shown in Table 1.[67]

Compulsory contributions are made by employers and subject neither to personal nor to corporate income tax. They are taxed at a flat rate of 15% when they enter the fund (compared to a modal marginal income tax rate of 34.5% and a top rate of 47%). People can contribute voluntarily up to an additional $27,500 per year pre-tax and $100,000 post-tax (both also attracting the standard 15% tax on entry). Before the retirement phase, cash returns on Super are taxed at 15% and capital gains at 10%, levied on the fund. Withdrawal is prohibited until age 58 if retired (rising to 60 by 2024) or 65 if still working, and is tax-free.[68] All returns generated during the retirement phase are untaxed.

Super is not paid on welfare payments, including paid parental leave. Sole traders do not have to make Super contributions for their own earnings. Historically, Super payments were compulsory for all workers with gross earnings of at least $450 per month, with this minimum recently removed. Super is paid on "ordinary time earnings", which is the gross amount the employee earns for their ordinary hours of work (before tax). It includes commissions, allowances, and bonuses, but excludes overtime.

For almost everyone, Super is highly tax advantaged relative to other forms of saving,[69] at the cost of being perfectly illiquid until retirement. Super is the only form of pre-tax saving, and cash returns to all other forms of savings are taxed at full marginal personal rates (more than two times the Super tax rate for the median taxpayer and more than three times for those in the top 3.6%). This includes interest, dividends, and rental income from investment properties. All capital gains (held for more than a year and excluding the primary residence) are taxed at half the marginal income tax rate (17.25% for the median individual and 23.5% for those in the top 3.6%) upon realization. Australia does not have a step-up in basis for

[65] All details in this subsection can be found on the website of Australia's tax authority: `https://www.ato.gov.au`.

[66] On all wage earnings up to $240,880 per year.

[67] Because Super was introduced in 1983 and the mandatory contribution amount has increased over time, the median balance in the cross section increases less with age than the median currently young person can expect their own balance to increase over their working life.

[68] There are limited circumstances in which working-age people can access their Super early. See: `https://www.ato.gov.au/individuals/super/withdrawing-and-using-your-super/early-access-to-your-super/`

[69] The one exception is the primary residence, which is untaxed (but mortgage interest on the primary residence is not tax-deductible) and does not affect eligibility for the public pension (described later).

inherited assets.[70]

Employers allocate employees to a default fund, but employees can instead nominate an alternative fund, and recent reforms have encouraged competition between and consolidation across funds. Within their nominated Super fund, account holders can typically choose an investment strategy with a particular risk–return trade-off. Super funds invest in listed assets but also make direct investments in unlisted assets like infrastructure. People can also manage their own Superannuation savings via a 'self-managed Super fund', with around 3% of all Super account holders doing so.

There are $3.5 trillion (160% of GDP) in total Super assets, constituting one of the largest private pension pools in the world.[71] Over the past decade, the median 'growth' fund has achieved an average annual return of 9.5% after taxes and fees. Over the 29 years the Super system has existed, the average annual return has been 8.3%, with four years posting losses (the largest of which was 21.5% in 2008).[72] There are 128 Super funds, many of which were initiated by the labor movement ('industry' funds), which agitated for the establishment of the Super system.[73] In Australia, the Superannuation system is strongly affiliated with the centre-left Australian Labor Party, which introduced the system. The centre-right Liberal Party government, which introduced the early Super release program, would later propose that first-home buyers be able to access Super for a home deposit. This was strongly opposed by the then-Labor-Opposition on the basis that early access undermines the Super system.

Alongside Super, Australia also has a public pension system paying up to around $900 per fortnight to those aged 67 or older, a rate which is means-tested on the basis of current income and assets (including Super but excluding the primary residence). For those who own their own home and with assets of more than $280,000 ($419,000 for couples), every $1,000 in additional Super reduces the pension for which they are eligible by $3 per fortnight. This means those with assets of more than $609,250 ($915,500 for couples) are ineligible to receive a public pension.

[70]Other than the primary residence of the deceased, which remains exempt from capital-gains tax provided it is sold within two years.

[71]https://www.oecd.org/daf/fin/private-pensions/Pension-Funds-in-Figures-2021.pdf

[72]https://www.superguide.com.au/comparing-super-funds/super-funds-returns-financial-year

[73]See Mees (2017) for a history of the establishment of the Superannuation system.

B Eligibility

In Section 3, we compared those who withdrew with those who did not without regard for the eligibility conditions of the program. While the tax authority administering the program appears not to have engaged in any systematic compliance or enforcement activity, *ex ante* participants may have expected it to do so, or felt a moral obligation to conform to the rules. The application process generated very little friction, requiring the applicant to fill out a short online form but not requiring them to substantiate their eligibility in any way. The funds were then deposited into the applicant's bank account in just a few days.

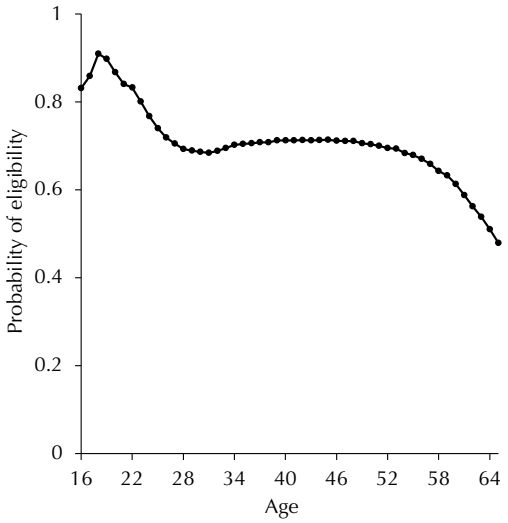
During the application process, applicants had to nominate a criterion according to which they were eligible. In the first withdrawal, 48% stated a reduction in working hours, 19% each being unemployed and being eligible to receive a government benefit (government payments go to more than a quarter of the population, akin to the US Child Tax Credit), 9% being a sole trader shut down or with a reduction in turnover, 3% having been made redundant, and 2% being a visa holder facing hardship. We do not observe a withdrawer's true eligibility, nor whether they believed they were eligible. But because we observe weekly wage earnings and welfare payments, we can construct a proxy for eligibility which would seem to reasonably approximate the three largest and fifth-largest categories, covering 89% of applicants according to their self-nominated reason for eligibility. Consistent with the eligibility conditions listed in Appendix A, we define someone as eligible if they experienced a 20% decline in weekly wages or received a welfare payment between January 8 and June 25.

According to this measure, 70% of the population were eligible to withdraw Super.[74] While 17% of the working-age population withdrew Super, 20% of those eligible withdrew, and 11% of those ineligible withdrew. This suggests 18% of those who withdrew were ineligible—or, put differently, the compliance rate was 82%. One potential limitation is that we don't observe hours, only earnings. It is possible, however unlikely, that an observed reduction in wages is due to a reduction in the wage rate rather than hours, upon which eligibility was contingent. But while that means our measure could exclude some who are eligible, it also means it could include some who are ineligible. We also don't observe business turnover or visa status, which may have triggered eligibility for sole traders and foreign workers, respectively. But if we exclude the 11% claiming sole-trader or visa eligibility, the compliance rate is a little higher at 86%.

The main concern about eligibility is that it might explain the observed differences between those who withdrew and those who did not. For example, welfare recipients may both have

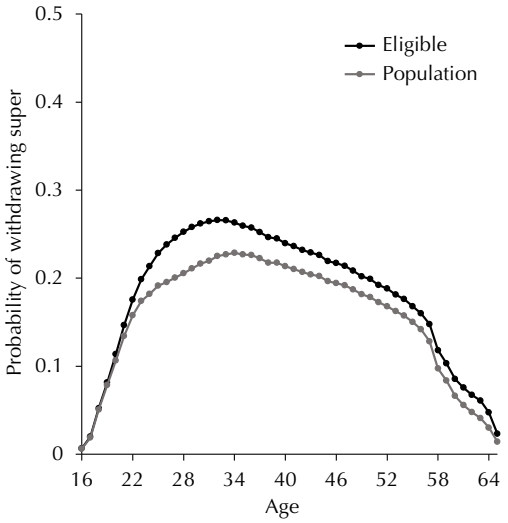
[74] An Australian National Audit Office audit of Australian Taxation Office (ATO) program administration notes that by mid-June 2020 the ATO was able to reach a high degree of confidence with respect to the eligibility of around 70% of applicants. By end-July the ATO had assessed that around 90% were eligibility to apply, and under 0.02% of applications were affected by fraud. See: `https://www.anao.gov.au/work/performance-audit/the-australian-taxation-office-management-risks-related-to-the-rapid-implementation-covid-19`.

Figure A1: The relationship between eligibility and age



(a) Probability of eligibility conditional on age

Data: Ilion
Notes: First withdrawal. Individual-level MPXs estimated via simple difference in spending three weeks before and after withdrawal. Bin size is 0.05.



(b) Probability of withdrawal conditional on age

Data: Ilion
Notes: First withdrawal. Individual-level MPXs estimated via simple difference in spending three weeks before and after withdrawal. Bin size is 0.05.

lower liquidity than non-welfare-recipients and be overrepresented among the withdrawers not by choice but by eligibility. To assess the effect of eligibility, we recompute Table 2 but among the eligible (Table A1). Note that we are unable to construct our eligibility proxy in the bank transactions data, so can only reproduce the items relying on our administrative data. While there are differences in levels because the eligible differ from the broader population, all of the same patterns observed in the general population are present among the eligible. There are negligible differences in demographics. The eligible non-withdrawers have higher wages and rental incomes and lower interest incomes, dividends, and voluntary Super contributions than the non-eligible non-withdrawers. The eligible withdrawers have higher wages and slightly lower interest incomes, rental incomes, dividends, and voluntary Super contributions than the non-eligible withdrawers, and almost identical Super balances. But, critically, eligibility does not affect the relationship between liquidity and withdrawal—all of the differences have the same directions and similar magnitudes.

The relationship between age and withdrawal is only mildly affected by eligibility. In Figure A1a, the probability of eligibility is around 70% from the mid 20s to late 50s. Eligibility is significantly higher for those in their late teens and early 20s due to a greater probability of having a reduction in working hours or being in receipt of a government benefit (due to the prevalence of the Youth Allowance payment). As shown in Figure A1b, this translates into a probability of withdrawal among the eligible that has a very similar profile.

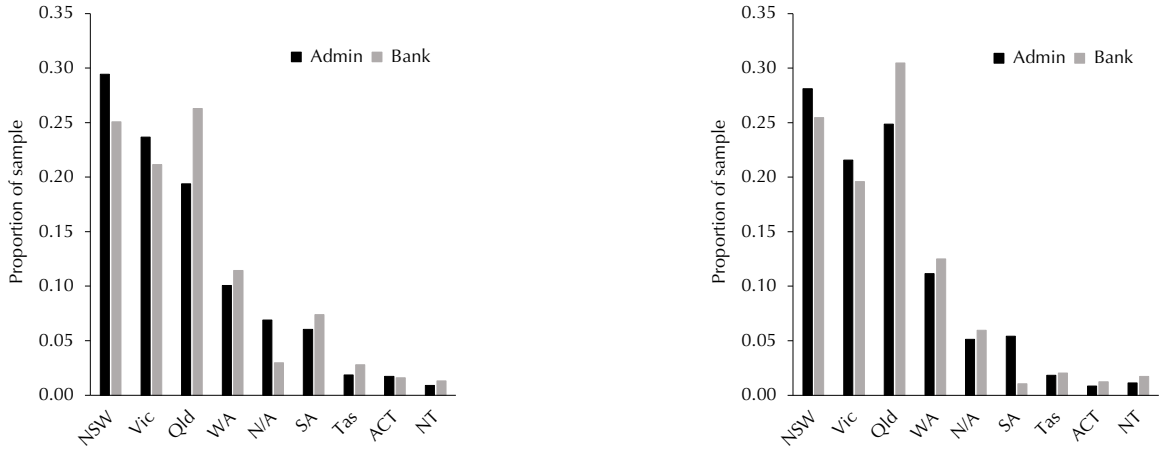
Table A1: Estimated differences in means between eligible withdrawers and non-withdrawers for first withdrawal

	Non-withdrawer	Withdrawer (difference)			
Controls	None	None	Wages	Plus age	Plus all
Demographics					
Age	40.09	-2.16	-1.67		
	(0.00)	(0.01)	(0.01)		
Female	0.50	-0.06	-0.09	-0.08	
	(0.00)	(0.00)	(0.00)	(0.00)	
Had spouse	0.54	-0.11	-0.09	-0.07	
	(0.00)	(0.00)	(0.00)	(0.00)	
Had kids	0.38	0.07	0.09	0.10	
	(0.00)	(0.00)	(0.00)	(0.00)	
Long-term financials					
Wages	57,973	-11,051			
	(18)	(40)			
Super balance	117,658	-57,560	-39,575	-31,669	-30,830
	(65)	(145)	(130)	(120)	(121)
Interest income	343	-253	-219	-203	-185
	(1)	(2)	(2)	(2)	(2)
Rental income	1,014	-461	-239	-213	-190
	(1)	(3)	(3)	(3)	(3)
Dividends	801	-632	-468	-418	-394
	(3)	(8)	(8)	(8)	(8)
Voluntary Super	1,807	-1,569	-1,412	-1,221	-1,109
	(4)	(9)	(9)	(9)	(9)
N = 10,675,214					

Data: Australian Taxation Office.
Notes: Results are from simple linear regressions of outcomes on a binary first-withdrawal indicator, controlling cumulatively for the 'Demographics' variables, and only among those eligible according to our proxy. Wage control for Demographics and Long-term Financials is average pre-tax wage income in the prior three years. Demographics are from the tax return in the financial year prior to withdrawal (July 1, 2018–June 30, 2019). Long-term financials except Super Balance and Voluntary Super are averages across the three prior tax returns (2016–17, 2017–18, and 2018–19). Super balance is as at June 30, 2019. Voluntary Super contributions are for the prior year (2018–19). Short-term wages are from Single-Touch Payroll records and cover average pre-tax wages in the month before withdrawal.

C Data comparison

Figure A2: State distribution by sample

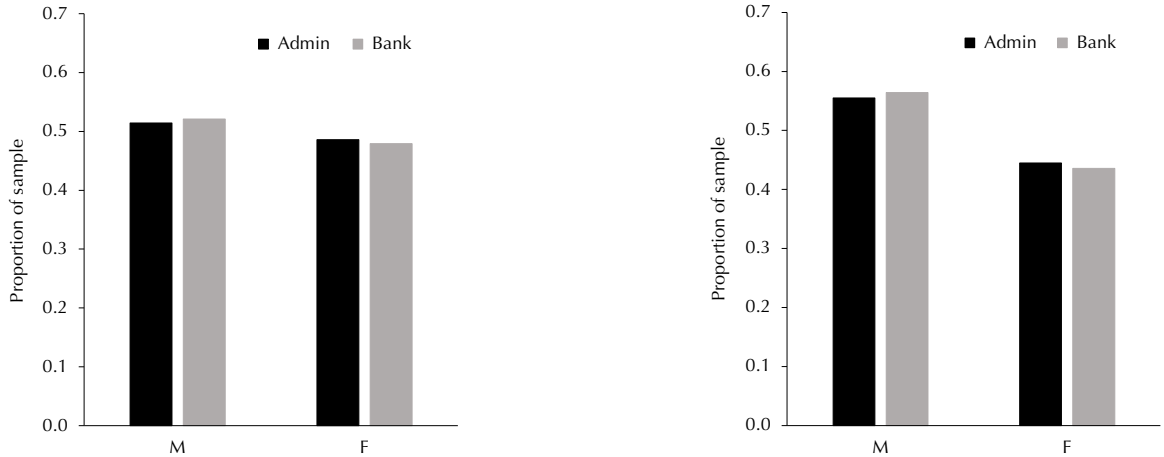


(a) Everyone

(b) Withdrawers

Data: Australian Bureau of Statistics and Illion
Note: Illion data are predicted based on transactions. Among the entire sample, location distributions are broadly similar, with Queensland overrepresented. Among the withdrawers, the two samples are more closely matched given Queensland is overrepresented among the withdrawers in the population.

Figure A3: Sex distribution by sample

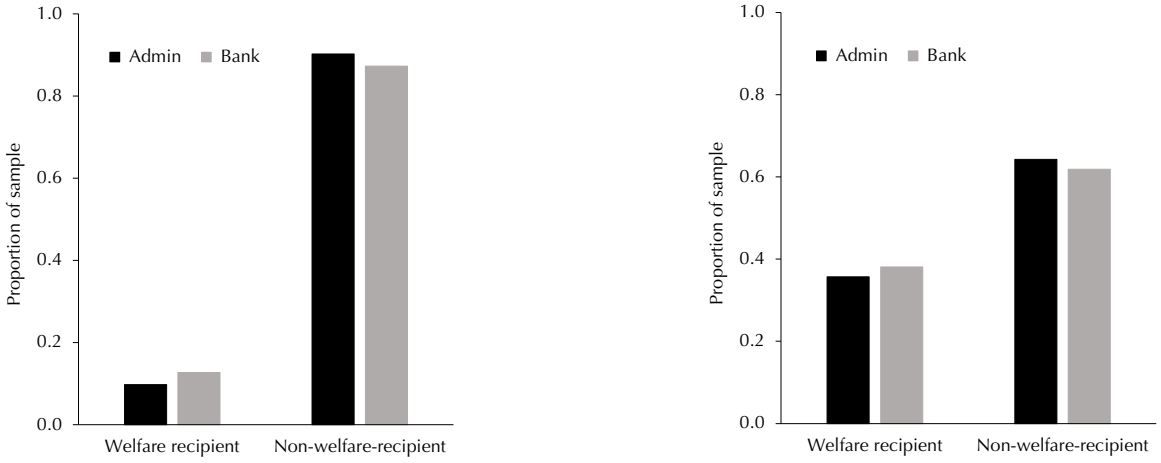


(a) Everyone

(b) Withdrawers

Data: Australian Bureau of Statistics and Illion
Note: Illion data are predicted based on transactions. Among the entire sample, the sex shares are similar (the self-employed, who are more likely to be male, are less likely to have Super and thus not to be in the population). Among the withdrawers, the shares continue to be similar despite the skewing towards men in the population.

Figure A4: Welfare receipt distribution by sample

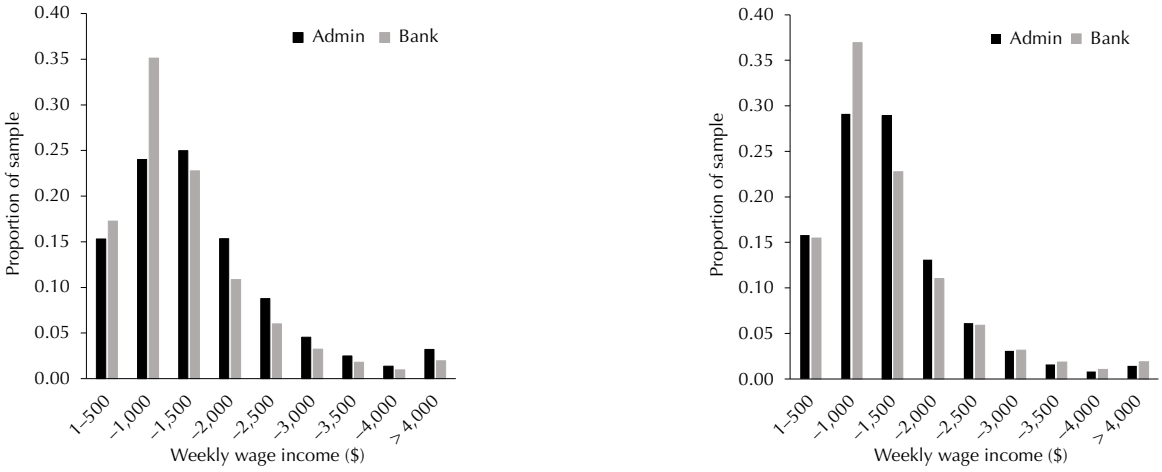


(a) Everyone

(b) Withdrawers

Data: Department of Social Services and Illion
Note: Welfare receipt defined as having been observed receiving a 'JobSeeker' payment. Among the entire sample, the welfare shares are similar, with a slight overrepesentation in the Illion data. Among the withdrawers, the shares are more similar despite the skewing towards welfare recipients in the population.

Figure A5: Wage distribution by sample



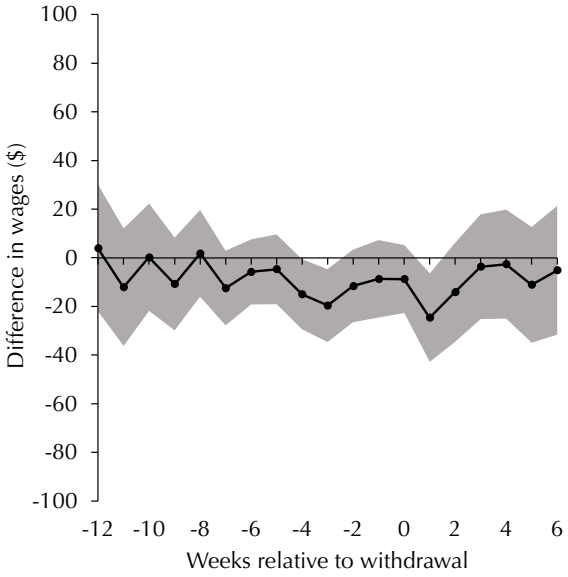
(a) Everyone

(b) Withdrawers

Data: Australian Taxation Office and Illion
Note: Average weekly wages in March 2020. ATO wages are pre-tax and Illion wages are post-tax, so the Bank wage distribution is shifted left by at least 18% for all weekly wage amounts in excess of $350 (tax-free threshold). Among the entire sample, the Bank data are less right-skewed, being more concentrated around the mode. Because this is true for the withdrawers in the population, the withdrawer distributions are quite closely matched.

D Wage event study

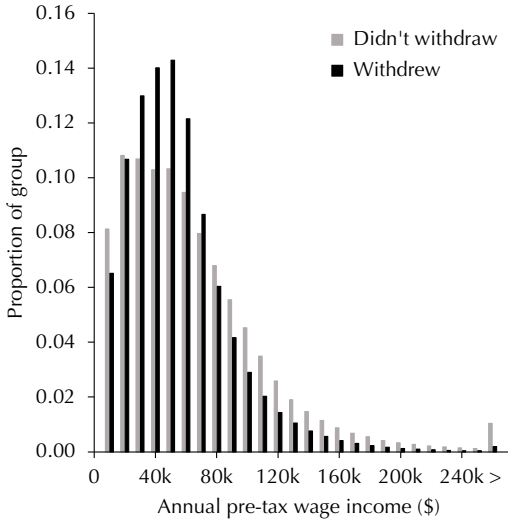
Figure A6: Relationship between wages and withdrawal timing



Data: Australian Taxation Office
Notes: Results are averages of cohort ATTs in Figure 6 weighted by cohort size, estimated via the R package, 'did', which implements Callaway and Sant'Anna (2021). Comparison group is the never-treated. Estimation is 'doubly-robust', with standard errors computed using the bootstrap procedure of Callaway and Sant'Anna (2021). Confidence intervals are at the 95% level.

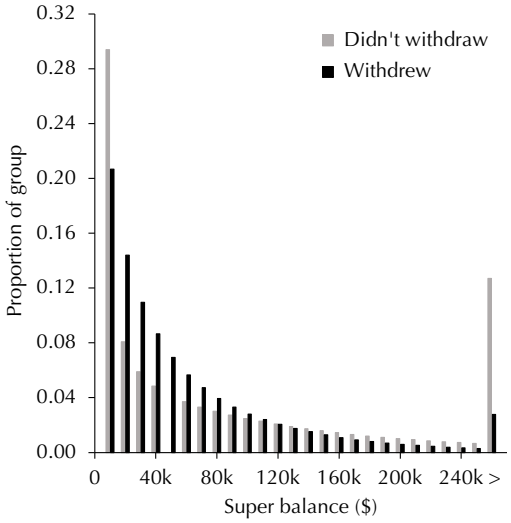
E Wage and Super balance densities

Figure A7: Histograms of Super and wages by withdrawal status



(a) Wage histogram by withdrawal status

Data: Australian Taxation Office
Notes: Wage income is average of the prior three financial years (2016–17, 2017–18, and 2018–19). Bin size is $10k, first bin includes $0, top bin is >$250k.



(b) Super histogram by withdrawal status

Data: Australian Taxation Office
Notes: Super balance is as at June 30, 2019. Bin size is $10k, first bin includes $0, top bin is >$250k.

F Withdrawal rate by occupation

Table A2: Withdrawal rate by occupation

Occupation	Withdrew (%)
Construction and Mining Labourers	40.2
Mobile Plant Operators	36.7
Factory Process Workers	35.0
Machine and Stationary Plant Operators	32.9
Other Labourers	32.6
Food Trades Workers	32.4
Storepersons	32.0
Road and Rail Drivers	30.1
Construction Trades Workers	29.0
Cleaners and Laundry Workers	27.2
Automative and Engineering Traders Workers	26.4
Other Technicians and Trades Workers	26.2
Hospitality, Retail and Service Managers	25.3
Health and Welfare Support Workers	24.7
Sports and Personal Service Workers	24.6
Hospitality Workers	23.7
Carers and Aides	23.1
Farm Forestry and Garden Workers	22.4
Sales Representative and Agents	22.3
Skilled Animal, Agricultural and Horticultural Workers	21.4
Inquiry Clerks and Receptionists	20.4
Sales Support Workers	19.9
Sales Assistants and Salespersons	18.9
Food Preparation Assistant	18.7
Other Clerical and Administrative Workers	18.5
Electrotechnology and Telecommunications Traders Workers	17.8
Outside Labour Force	17.6
Clerical and Office Support Workers	17.0
Protective Service Workers	16.7
Farmers and Farm Managers	16.6
Engineer, ICT and Science technicians	16.0
Arts and Media Professionals	14.5
Numerical Clerks	14.4
Chief Executives, General Managers and Legislators	14.2
General Clerical Workers	14.1
Office Managers and Program Administrators	13.9
Specialist Managers	13.4
Personal Assistants and Secretaries	13.2
Business, HR and Marketing Professionals	11.8
Health Professionals	10.5
Legal, Social and Welfare Professionals	9.4
Design, Engineering, Science and Transport Professionals	8.9
ICT Professionals	7.2
Education Professionals	6.3

Data: Australian Taxation Office
Note: Occupation based on tax return in prior financial year.

G Week of withdrawal regressions

Table A3: Relationships between observed variables and week of withdrawal during the first round

	Withdrew 1 May	Average change per week of withdrawal delay			
Controls	None	None	Wages	Plus age	Plus all
Wages	43,975	427			
	(55)	(15)			
Age	37.76	0.20	0.19		
	(0.02)	(0.00)	(0.00)		
Super balance	54,299	2,337	1,919	1,348	1,357
	(130)	(35)	(32)	(29)	(29)
Interest income	93.64	4.89	4.70	3.88	3.54
	(1.50)	(0.40)	(0.40)	(0.40)	(0.40)
Rental income	537.99	24.27	17.49	13.89	11.92
	(5.07)	(1.36)	(1.34)	(1.34)	(1.34)
Dividends	203.37	20.91	20.10	16.68	16.52
	(7.39)	(1.99)	(1.99)	(1.99)	(1.99)
Voluntary Super	225.86	24.83	22.96	19.62	19.90
	(4.20)	(1.13)	(1.13)	(1.13)	(1.13)
N = 1,172,034					

Data: Australian Taxation Office
Notes: Results are from simple linear regressions of listed outcomes on a category variable for withdrawal week during the first round (May 1 is zero and for subsequent weeks the indicator increases by one), controlling cumulatively for the wages and 'Demographics' variables listed in Table 2. The first and last weeks of the first withdrawals are excluded. This estimates the average increase by withdrawal week in pre-treatment characteristics controlling for wages and demographics; that is, whether the upward-sloping lines in Figure 4 remain upward sloping when we condition on wages and demographics. Note all coefficient estimates are positive and statistically significant at the 99% level or above. Variable definitions as per 'Demographics' and 'Long-term financials' in Table 2.

H Estimated average treatment effects on the treated

Table A4: Estimated ATTs on income of the first withdrawal

Week	Cohort								
	1	2	3	4	5	6	7	8	All
0	9,311.75	9,508.25	9,148.29	8,867.91	8,717.52	9,074.77	8,588.43	8,470.03	9,187.90
	(70.61)	(109.90)	(246.41)	(134.49)	(438.35)	(259.33)	(338.74)	(187.82)	(56.36)
1	121.26	345.18	238.20	219.74	-8.21	121.38	-205.44		166.35
	(56.10)	(64.98)	(81.01)	(83.84)	(280.05)	(130.61)	(157.48)		(36.10)
2	-127.72	402.63	157.62	463.05	-343.39	-124.70			54.44
	(170.12)	(77.41)	(97.77)	(178.25)	(314.98)	(135.81)			(88.37)
3	-71.44	191.60	161.68	46.11	-293.86				6.65
	(47.48)	(66.47)	(107.89)	(61.50)	(279.96)				(36.17)
4	-127.95	295.55	89.81	92.11					17.50
	(62.42)	(55.75)	(154.85)	(85.98)					(41.58)
5	28.69	196.57	79.46						77.92
	(61.06)	(85.19)	(102.71)						(45.02)
6	-126.59	235.86							-16.98
	(98.42)	(95.40)							(74.96)
7	-151.02								-151.02
	(63.47)								(63.47)
Pr	0.43	0.19	0.10	0.09	0.06	0.05	0.04	0.03	1

Data: Illion
Notes: N = 337,223. Results are cohort ATTs estimated via the R package 'fixest', which implements Sun and Abraham (2021). Comparison group is the never-treated. Base period is the period immediately prior to treatment. Standard errors computed via a standard bootstrap procedure. Probabilities listed are cohort shares, which for each week are used to compute the weighted averages across cohorts in the right-most column.

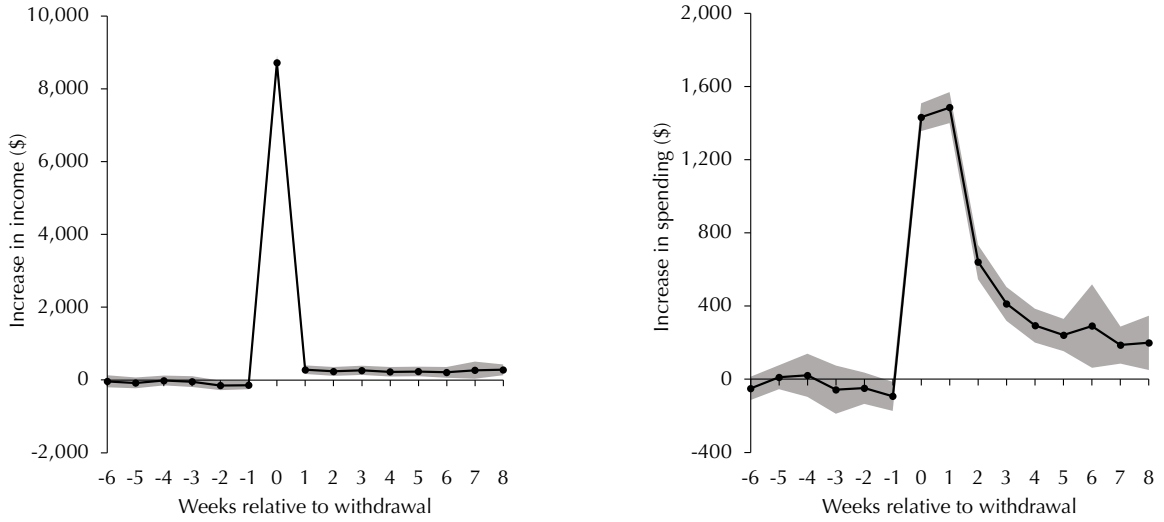
Table A5: Estimated ATTs on spending of the first withdrawal

Week	Cohort								
	1	2	3	4	5	6	7	8	All
0	1,676.14	1,488.76	1,502.21	1,508.68	1,414.70	1,498.56	1,471.85	1,545.65	1,569.85
	(24.98)	(34.33)	(50.44)	(47.27)	(62.42)	(68.94)	(78.12)	(82.06)	(16.10)
1	1,229.40	1,344.43	1,384.28	1,313.06	1,252.23	1,295.65	1,217.15		1,279.86
	(19.58)	(30.81)	(46.20)	(43.88)	(54.07)	(66.72)	(71.88)		(13.26)
2	472.92	544.20	551.52	519.32	476.52	499.47			501.74
	(14.94)	(23.50)	(33.98)	(34.52)	(43.07)	(51.34)			(10.53)
3	247.78	303.65	346.69	306.09	284.20				278.13
	(13.36)	(21.91)	(32.48)	(31.10)	(42.99)				(9.77)
4	150.68	212.25	244.18	238.27					184.19
	(14.99)	(22.61)	(35.28)	(37.66)					(11.24)
5	134.43	133.79	160.12						137.34
	(15.43)	(24.13)	(36.34)						(12.35)
6	55.69	89.95							66.05
	(16.34)	(25.38)							(13.51)
7	15.58								15.58
	(16.92)								(16.92)
Pr	0.43	0.19	0.10	0.09	0.06	0.05	0.04	0.03	1

Data: Illion
Notes: N = 337,223. Results are cohort ATTs estimated via the R package 'fixest', which implements Sun and Abraham (2021). Comparison group is the never-treated. Base period is the period immediately prior to treatment. Standard errors computed via a standard bootstrap procedure. Probabilities listed are cohort shares, which for each week are used to compute the weighted averages across cohorts in the right-most column.

I Second withdrawal event study graph

Figure A8: Estimated ATT of the second withdrawal by event week



(a) Income

(b) Spending

Data: Illion

Notes: Results are averages of cohort ATTs weighted by cohort size, estimated via the R package, 'did', which implements Callaway and Sant'Anna (2021). Comparison group is the never-treated. Estimation is 'doubly-robust', with standard errors computed using the bootstrap procedure of Callaway and Sant'Anna (2021). Confidence intervals are at the 95% level. The 'did' package, by default, uses a 'varying' base period when estimating cohort ATTs for the pre-treatment periods, where the base period is the period immediately prior. This is why estimates for the period immediately prior to withdrawal (and their confidence-interval estimates) are not zero. For all post-treatment estimates, the period immediately prior to treatment is used as the base period. There was a permanent increase in income post-withdrawal. Because withdrawals occurred from July 1, they coincided with the start of the new financial year in Australia, typically when people receive a pay rise, a higher government benefit linked to inflation, or a tax refund. This income difference may reflect differences between withdrawers and non-withdrawers on these bases. By dividing the estimated spending impact by the estimated income impact when calculating the MPX, we remove upward bias driven by these other sources of income.

J Category regression table

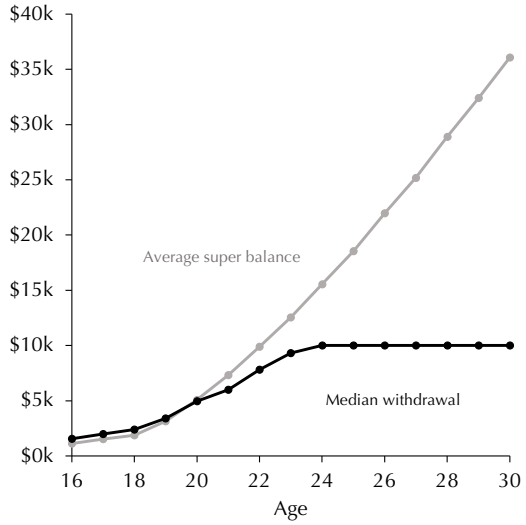
Table A6: Estimated cumulative aggregate ATTs (CAATTs) of the first withdrawal by category

Category	CAATT	Category	CAATT
Uncategorized	1,248.87***	Alcohol and Tobacco	32.27***
	(81.41)		(6.18)
ATM	1,063.88***	Retail	31.58***
	(71.04)		(4.90)
Other debt repayments	339.95***	Health services	15.54***
	(45.37)		(5.16)
Gambling	292.98***	Pharmacies	13.82***
	(30.21)		(3.76)
Credit card repayments	196.70***	Personal care	13.21
	(28.87)		(15.52)
Furniture and office	168.06***	Taxi and rideshare	12.35***
	(14.59)		(2.82)
Supermarkets	128.80***	Travel	12.27*
	(19.45)		(7.32)
Department stores	114.73***	Education	11.47*
	(9.48)		(6.93)
Rent	98.51***	Post office	8.75**
	(37.88)		(4.10)
Buy-now-pay-later	94.49***	Pet care	7.21**
	(12.99)		(3.51)
Restaurants	79.02***	Cafes	6.11***
	(7.46)		(1.74)
Automotive	78.82***	Car rentals	5.97
	(12.25)		(4.58)
Online retail	72.29***	Children's retail	5.29
	(10.86)		(5.25)
Fashion and leisure	71.67***	Road tolls	4.75**
	(8.47)		(2.12)
Home improvement	71.42***	Insurance	4.34
	(15.90)		(10.53)
Gas stations	60.78***	Entertainment	3.98***
	(11.21)		(1.21)
Telecommunications	44.88***	Donations	3.06
	(11.81)		(2.35)
Government	39.95***	Subscription TV	2.84
	(12.17)		(2.40)
Utilities	36.26***	Gyms and fitness	2.06
	(10.35)		(1.55)
Food delivery	35.80***	Transport	-0.02
	(4.14)		(0.05)
Other groceries	35.76***	Public transport	-0.21
	(6.15)		(5.08)
N = 337,223			

Data: Illion
Notes: *** p < 0.01; ** p<0.05; * p <0.1. Results are based on cohort ATTs estimated via the R package 'fixest', which implements Sun and Abraham (2021). We compute weekly aggregate ATTs by averaging across cohorts weighted by cohort share. We then accumulate over the first eight post-treatment weeks. Standard errors are computed analytically as per Sun and Abraham (2021).

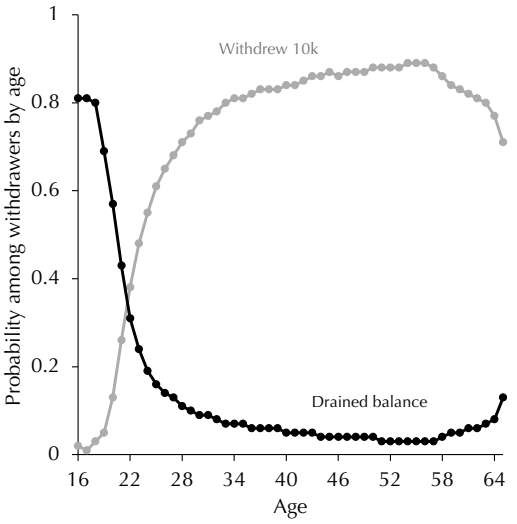
K Withdrawal and age

Figure A9: The relationship between age and withdrawal amount



(a) Super balance and withdrawal amount by age

Data: Australian Taxation Office
Notes: First withdrawal. Average Super balance as at June 30, 2019.



(b) Withdrawal cap and balance as constraints by age

Data: Australian Taxation Office
Notes: First withdrawal. Drained balance if first withdrawal amount equal to Super balance on June 30, 2019.