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# Who's Declining the "Free Lunch"? New Evidence from the Uptake of Public Child Dental Benefits

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# NON-TECHNICAL SUMMARY

This paper provides the first evidence on the determinants of uptake of two recent public dental benefit programs for Australian children and adolescents from disadvantaged families. Using longitudinal data from a nationally representative survey linked to administrative data with accurate information on eligibility and uptake, we find that only a third of all eligible families actually claim their benefits. These actual uptake rates are about half of the targeted access rates that were announced for them.

We provide new and robust evidence consistent with the idea advanced by recent economic literature that cognitive biases and behavioural factors are barriers to uptake. For instance, mothers with worse mental health or riskier lifestyles are much less likely to claim the available benefits for their children. These barriers to uptake are particularly large in magnitude: together they reduce the uptake rate by up to 10 percentage points (or 36%). Consistent with the evidence of behavioural barriers to uptake, the results also demonstrate that while prior preventive oral health behaviours affect the subsequent uptake, the child's previous dental health conditions do not. Furthermore, we find some indicative evidence that a lack of information may be an important barrier to uptake: children living in owned homes are significantly more likely to take up the benefits than those in rented homes. The results also suggest that there may be a welfare stigma obstacle to uptake of the two child dental benefit programs because eligible children from families with higher income or private health insurance take up less. However, other characteristics of the child or the mother and the supply-side of the dental services market do not explain these differences.

Our findings of factors shaping the uptake decision have some potentially important policy implications. For example, to the extent that policymakers view raising uptake as a policy objective, the results provide insight into which groups policies that aim to help disadvantaged children should target. While some of barriers identified in this paper, including cognitive biases and behavioural barriers, may not be easily overcome, several studies have shown it may be feasible to address them. For instance, the role of limited cognitive ability in non-uptake can be mitigated by reminders about eligibility or simplification, e.g., through a visually more appealing notice. Reducing such barriers to uptake among disadvantaged groups may also help to lessen the documented intergenerational transmission of disadvantages. Overall, the results thus produce insights into the operation of the programs that are relevant not only to the success of the current program, but also for policy initiatives to improve their uptake in a range of population sub-groups.

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# ABSTRACT

Recent economic literature has advanced the notion that cognitive biases and behavioural barriers may be important influencers of uptake decisions in respect of public programs that are designed to help disadvantaged people. This paper provides the first evidence on the determinants of uptake of two recent public dental benefit programs for Australian children and adolescents from disadvantaged families. Using longitudinal data from a nationally representative survey linked to administrative data with accurate information on eligibility and uptake, we find that only a third of all eligible families actually claim their benefits. These actual uptake rates are about half of the targeted access rates that were announced for them. We provide new and robust evidence consistent with the idea that cognitive biases and behavioural factors are barriers to uptake. For instance, mothers with worse mental health or riskier lifestyles are much less likely to claim the available benefits for their children. These barriers to uptake are particularly large in magnitude: together they reduce the uptake rate by up to 10 percentage points (or 36%). We also find some indicative evidence about the presence of the lack of information barrier to uptake. The results are robust to a wide range of sensitivity checks, including controlling for possible endogenous sample selection.



**Keywords:** government programs; impact evaluation; dental health; provision and effects of welfare programs; Australia; uptake; take-up



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## 1. Introduction

The issue of incomplete uptake (or "take-up") of social benefits, where individuals do not claim the benefits for which they are eligible, is well-documented (Currie 2006; Van Mechelen & Janssens 2017). Studies have also explored factors behind non-uptake and they are broadly classified into two strands of research (see, for example, Currie (2006) or Van Mechelen & Janssens (2017) for reviews). The first line of literature typically assumes that individuals are perfectly rational and therefore perfectly able to compare between costs and benefits of uptake (Moffitt 1983; Kleven & Kopczuk 2011). Consistent with this traditional theorical framework, research identifies three main obstacles to uptake, namely social stigma (Moffitt 1983; Holford 2015), the lack of information about eligibility (Bhargava & Manoli 2015; Liebman & Luttmer 2015; Guyton *et al.* 2017; Armour 2018; Barr & Turner 2018; Finkelstein & Notowidigdo 2019) and transaction costs associated with enrolment (Aizer 2007; Bettinger *et al.* 2012; Deshpande & Li 2019).

The second and more recent strand of uptake literature deviates from the traditional assumptions of rationality by implicating the role of cognitive biases and behavioural barriers (O'Donoghue & Rabin 1999). Studies from this line of literature highlight the role of non-monetary factors driving uptake such as the complexity of information available (Carroll *et al.* 2009; Saez 2009; Bhargava & Manoli 2015), the lack of understanding about costs and benefits (Bertrand *et al.* 2006) and the social interaction between individuals within a network (Mullainathan *et al.* 2000; Dahl *et al.* 2014). Although many policies have been employed to improve uptake, the feature of low uptake remains a "continuing puzzle" (Currie 2006; Finkelstein & Notowidigdo 2019),[1] and further research is required to explore other factors that may drive non-uptake.

In this paper, we report findings on the determinants of non-uptake of two recent public dental benefit programs for Australian children and adolescents from disadvantaged families. Five features of our setting make it appealing for study. First, this paper provides the first investigation into the determinants of participation in these programs. Second, we focus on the uptake of two public programs designed to improve developmental outcomes in young children where uptake decisions are made at the household level (Hastings & Weinstein 2008; Dizon-Ross 2019). This feature of two programs and the available data enable us to explore the role

[1] In their experiment, Finkelstein & Notowidigdo (2019) found that only about a third of elderly individuals who are likely to be eligible for the Supplemental Nutrition Assistance Program (SNAP) call in response to their outreach materials, suggesting a potential ceiling in the uptake rates.

of some potentially important factors that have not been investigated before in the literature. For example, we can document the role of cognitive biases and behavioural barriers to uptake originating from the parents of the eligible children. Third, we focus on two programs in which many of the traditional costs of uptake are particularly low and the benefits are quite substantial, leaving the low uptake problem especially mystifying. Indeed, unlike most means-tested public programs, eligibility for these two programs is automatic: eligible families do not need to complete an application or supply additional information in order to establish their eligibility (Currie 2006). Fourth, the linked survey-administrative panel data used in this study allow us to accurately measure the uptake of benefits (i.e., eligible claimants/eligible individuals), enabling us to overcome the limitation of the literature in measuring eligibility, uptake or both (Van Mechelen & Janssens 2017). Fifth, although we use a non-experimental research design we are able to test the robustness of our findings against various issues associated with studies of this kind, including endogenous sample selection, unobservable characteristics and self-reported data on eligibility. For instance, we address the issue of endogenous sample selection in benefit eligibility by employing a Heckman selection correction regression, exploiting the discontinuity in one of the main eligibility criteria as an exclusion restriction variable.

Our results show that less than a third of all eligible families claim dental benefits for their children. These represent uptake rates that are approximately half those the government hoped to achieve (Department of Health - DoH 2016). We provide new and robust evidence consistent with the ideas of cognitive biases and behavioural barriers in the uptake of public benefits. Mothers with worse mental health or riskier lifestyles are much less likely to claim the benefits for their children. These potential barriers to uptake are particularly large in magnitude as together they reduce the uptake rate by up to 10 percentage points (or 36% of an average uptake rate of 28% in our data). In line with the evidence of behavioural barriers to uptake, the results show that while prior preventive oral health behaviours influence the subsequent take-up of benefits, the child's previous dental health conditions do not.

We also find some indicative evidence that a lack of information may be an important barrier to uptake: children living in owned homes are significantly more likely to take up the benefits than those in rented homes. The results also suggest that there may be a welfare stigma obstacle to uptake of the two child dental benefit programs because eligible children from families with higher income or private health insurance take up less. However, other characteristics of the child or the mother and the supply-side of the dental services market do not explain these differences.

The rest of this paper proceeds as follows: Section 2 provides detailed information about the policies. We introduce our data in Section 3 and empirical method in Section 4. We present the main results in Section 5 and show results from various robustness checks in Section 6. In section 7, we conclude and discuss policy implications.

## 2. Background of public child dental benefit policies and uptake

The Australian Government introduced the Medicare Teen Dental Plan (MTDP) to improve dental health of teenagers in disadvantaged families in 2008, following the Dental Benefits Act 2008 and its subordinate Rules (DoH 2012). Under the MTDP, the Government provided dental benefits of up to Australian dollar (A$) 150 per calendar year[2] for each eligible teenager 12-17 years of age in families receiving Family Tax Benefit Part A (FTB A) or other relevant Australian Government payments[3] to receive a preventive dental check. The MTDP was replaced by the Child Dental Benefits Schedule (CDBS) in 2014. According to this Schedule, to be eligible, a child must be aged between 2 and 17 years and their family must receive FTB A or other relevant Australian Government payments (DoH 2019a). The CDBS provides funding to cover the cost of essential preventive and restorative treatments up to a value of A$1,000 over a two consecutive calendar-years period. Benefits cover a range of dental services, including examinations, x-rays, cleaning, fissure sealing, fillings, root canals, extractions and partial dentures. However, benefits are not available for orthodontics, cosmetic dental work or high-level restorative services. Services may be provided by public or private dental practitioners who participate in the program. Thus, as compared to its predecessor, the CDBS offers broader age-based coverage (i.e., children aged between 2-17 years versus children aged between 12-17 years in MTDP) as well as much more generous benefits (i.e., A$1,000 over a two consecutive calendar-years period versus A$150 per calendar year).[4]

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[2] The benefit was indexed yearly, reaching A$166.15 in the final year of MTDP in 2013 (DoH 2016).

[3] Other relevant Australian Government payments include Youth Allowance, ABSTUDY, Disability Support Pension, Parenting Payment Special Benefit, Carer Payment, Double Orphan Pension, Veteran's Children Education Scheme, and Military Rehabilitation and Compensation Act Education and Training Scheme (if the child is 16 or over). In Australia, FTB A is a government payment to eligible families to help with the cost of raising children. To be eligible, families must meet an income test and residence rules. In turn, the income test varies by the ages and number of children (see Appendix Table A4 for an example). As of Financial Year (FY) 2014-15, the maximum annual rate for FTB A was A$6,723.30 per child. In Australia, the financial year runs from 1st July to 30th June of the following year. Almost all (97%) children were eligible to dental benefits because their families received FTB A (DoH 2016).

[4] The stakes associated with non-uptake are nontrivial for the children and their families as average annual CDBS benefits are about A$500, accounting for roughly 0.6% of household income among the eligible in 2014. At some point during the course of the CDBS, the Australian Government considered discontinuing it or changing its provisions (ANAO 2015). The Schedule was, however, still in effect at the time of writing (DoH 2019a).

A child's eligibility is evaluated by the relevant federal departments from the start of each calendar year and a notification of eligibility is sent to the child or the child's parent/guardian either electronically or by post.[5] The eligibility notification typically confirms eligibility into the program, summarizes the program and explains how to access the benefits. For the first program, the eligibility notification is in the form of a voucher (see Appendix Figure A1) while it is a notification letter in the second program (Appendix Figure A2).[6] Children may become eligible at any point in the calendar year and, once assessed as such, remains eligible for the remainder of that year (i.e., irrespective of subsequent changes in household circumstances) (DoH 2019b). Note that, by design, both programs have automatic enrolment which would be expected to enhance uptake, compared with the counterfactual, as has been found previously in the literature (Madrian & Shea 2001; Currie 2006).

[Insert Figure 1 here]

The temporal development of these public dental programs is shown in Figure 1. Figure 1 illustrates the fact that the targeted uptake rates were set quite high (e.g., 55% and 78% in the first year of MTDP and CDBS, respectively) in the first few years of both programs, before being lowered in subsequent years.[7] Furthermore, despite the Government's attempts to increase the uptake rates, including a substantial increase in the generosity in dental benefits from MTDP to CDBS, the actual uptake rates remained relatively stable, ranging between 29.4% (in FY 2014-15) and 37.1% (in FY 2017-18). Noticeably, the actual uptake rates were consistently lower than those targeted. While the problem of low uptake has been well-documented in previous governmental evaluations (DoH 2009, 2012; ANAO 2015; DoH 2016), those reports are silent on which eligible households are (un)likely to take up services under these public programs. Yet the factors that drive uptake decisions are critical for policy-

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[5] Currently, the Department of Human Services (DoHS) oversees issuing the eligibility notification. DoHS relies on the child's eligibility for the calendar year obtained from Centrelink, which is Australia's public welfare agency (administering age and disability pensions, unemployment benefits, and so on). Centrelink, in turn, uses the parent's family income estimates for the current financial year or actual family income in the previous financial year from the Australian Tax Office (ATO) to identify the child's eligibility. From 2015, eligibility notifications were also made electronically available on myGov (at https://my.gov.au) for users who have linked their Medicare record to their myGov account. Between 1 January and 30 June 2015, about 25% of notifications were issued through myGov (DoH 2016).

[6] Information about the programs is also made available at some dental practitioners' practices via posters or pamphlets (see Appendix Figure A3 for an example).

[7] The 2014–15 Budget Statement identifies a target of 2.4 million children accessing the CDBS, which would equate to an uptake rate of 78%. The targeted number of children participating in the CDBS was set at 2.4 million in the following financial year of 2015-16 before being reduced to 1.11 million in FY 2017-18. The figure was increased in the following years, reaching 1.22 million children (or 37.8% of all eligible children) in FY 2019-20. Unfortunately, the unavailability of data on the number of eligible children prevents us from calculating the targeted and actual uptake rates for all years.

makers to understand if the delivery of public policies to help under-served populations is to be improved. This is the focus of the current paper.

## 3. Data

The primary dataset for this study comes from the Longitudinal Survey of Australian Children (LSAC). The LSAC is a biennial nationally representative survey. The LSAC commenced in 2004 and contains comprehensive information about children's developmental outcomes and socio-economic and demographic backgrounds of children and their parents. The sampling frame consists of all children born between March 2003 and February 2004 (the Birth or B-Cohort: 5,107 infants aged 0–1 year in 2004) and between March 1999 and February 2000 (the Kindergarten or K-Cohort: 4,983 children aged 4–5 years in 2004) (AIFS 2018). We use the latest LSAC Release 7, from the 2016 survey, at which point children and their parents had been surveyed up to seven times. The panel nature of these data, in addition to the timing of the LSAC, allow us to observe the possible eligibility, uptake and child development outcomes both before and after the introduction of the MTDP or CDBS (see Appendix Table A1) and help us to reduce the effects of confounders on our central results. More importantly, the LSAC dataset is linked with several administrative datasets that provide detailed information on (i) whether the child is eligible for the MTDP or CDBS and (ii) their actual service use and benefits paid under the MTDP or CDBS. Combined, these data provide us with a richness of options with which to address the central econometric considerations alluded to above (and explored further in the coming sections of the paper).

### *3.1. Eligibility*

We use the child's age, the family's income support history (ISH) and the timing of MTDP or CDBS to identify the potentially eligible children among all surveyed children in the data. Specifically, we use the child's exact date of birth to identify their age-based eligibility in any given calendar year. In addition, information on types of government payment that the family received at the time of survey[8] is used to identify whether the child is eligible according to the program's means-test. However, because uptake is measured annually (more on this in Section 3.2) while variables used to calculate means-test eligibility are recorded biennially, we use the following rules (we denote them "Eligibility Rule 1" to distinguish them from other alternatives that we will use in Section 6.2) to overcome the timing gaps in survey and administrative data.

[8] Specifically, we use responses to the question "Does … (or partner) currently receive any of these Government benefits, allowances or other forms of assistance?" which is asked of Parent 1, in almost all cases the mother of the study child, in all survey waves.

Specifically, we identify the child's eligibility in terms of a means-test using the family's government payment history recorded at the same year as the calendar year of access to the child dental benefit recorded in the administrative data. In the event that the LSAC survey was not undertaken in the uptake year, we use the means-test eligibility measures reported by the household during the survey year prior to the year of uptake. The detailed matching rules we apply are described in Appendix Table A2.

### *3.2. Uptake of child dental benefits*

Access to the MTDP or CDBS is calculated from the administrative data linked to the LSAC data. Specifically, we use linked data from Medicare Benefit Scheme (MBS) and the Pharmaceutical Benefit Scheme (PBS) which record all Australian Government subsidies for medical services and pharmaceuticals under Australia's universal and compulsory Medicare scheme.[9] MBS and PBS data are linked for almost all (97%) LSAC children and are available from their births to March 2017 (AIFS 2018). The MBS and PBS datasets include a child identification number and the Medicare item numbers, item names, and dollar value of benefits (i.e., subsidies) paid, as well as the date of payment and date of service. We use the eligible MBS item numbers suggested by the Department of Health to identify the child's access to the MTDP or CDBS (DoH 2019b). As the amount of dental benefits available is capped over the calendar year, actual access to dental benefits is measured as the benefits paid per calendar year.

[Insert Table 1 here]

Table 1 reports the eligibility and uptake of public dental benefits by LSAC children between 2011 and 2016. Over this period, 41% of LSAC children are identified as eligible for either the MTDP or CDBS and 28% of eligible households actually took up the benefits.[10] This calculated

[9] Under the MBS, subsidies are provided for all approved private fee-for-service medical services provided both in- and out-of-hospital. The PBS provides subsidies for all pharmaceuticals that have been approved for public subsidy.

[10] Our data also show that, during the same period, about 9.8% of children identified as "ineligible" did take up the benefits. As access to the benefits is measured from administrative data, this uptake pattern among "ineligible" children should not be interpreted as "leakage" of the programs. Rather it is probably linked to the issues of (i) the timing gaps between surveyed and administrative data as discussed in Section 3.1 or (ii) the potential reporting errors in the self-reported ISH. This prediction is supported by the fact that using administrative ISH data which are reported annually and arguably free of reporting errors to identify eligibility (more on this in Section 6.3) only 3.6% of K-cohort children identified as "ineligible" took up the benefits. In Section 6.2 we will check the robustness of our results when these "ineligible" children are included in regressions. It should be noted that, while Government payments and taxable income are calculated on a financial year basis, eligibility and access to public child dental benefits are calculated on a calendar year basis. The timing differences, which may contribute to the issue of accurately identifying eligible children using surveyed data as detailed above, will be accounted

uptake rate is very close to the uptake rates reported in Figure 1 using administrative aggregate data sources (DoH 2016). Table 1 also indicates that the proportion of children eligible for child dental benefits decreased overtime, a pattern consistent with the fact that parents, especially mothers, return to work when their children grow up and hence their families become ineligible for government means-tested benefits. Furthermore, the uptake rate was lowest in 2011, most likely because it is the time when most K-cohort children became eligible for the MTDP, and is lower for MTDP than CDBS. In line with the design of the MTDP, conditional on any access to the MTDP, each child had exactly one dental (occasion of) service paid by the program per year and the amount of benefit paid is usually the same as the annual cap. In addition, and as expected, children eligible for CDBS had greater access to public benefits in terms of the amount of benefits as well as the number of dental services (1.7 per year) paid for by the scheme.

## 4. Empirical models

Focusing on a sample of potentially eligible children, the following empirical regression is estimated to examine the factors associated with the uptake of the benefits:

$$A_{i,t} = \alpha + X_{i,t}\beta + Y_{i,t-1}\gamma + \varepsilon_{i,t} \quad (1)$$

In equation (1), $A_{i,t}$ denotes the uptake of benefits by child $i$ at year calendar $t$, $X_{i,t}$ is a set of basic controls, $Y_{i,t-1}$ is a set of extended controls, $\varepsilon_{i,t}$ is a random error term, and $\alpha$, $\beta$ and $\gamma$ are sets of parameters to be estimated.

We include in $X_{i,t}$ a comprehensive list of variables that potentially explain the child's access to public benefits such as the child's characteristics (i.e., age and its square, gender, migration status, ethnicity, birth weight, breast-feeding history, number of siblings, whether the child lived with both parents), parental characteristics (i.e., age and its square, education and migration status) and neighbourhood characteristics.[11] Parental characteristics are included in our empirical model because parents are typically the decision-makers regarding the health

for in our empirical models by controlling for quarters of surveys in all regressions. To this end, this study shares a common challenge of identifying eligibility and uptake as documented in previous studies (Blank & Ruggles 1996; Daponte *et al.* 1999; Finkelstein & Notowidigdo 2019).

[11] In the baseline regressions, we mainly consider maternal characteristics because paternal characteristics entail significant missing information. Local variables include percentages of individuals with year 12 completions, speaking English, being born in Australia, identifying as being of Aboriginal/Torres Strait Islander (ATSI) origin, percentages of households with household income less than A$1,000/week in linked areas, and a metropolitan dummy. Some studies use local level variables to investigate the role of social networks in welfare participation (Mullainathan *et al.* 2000; Aizer & Currie 2004). We also control for possible temporal and geographical differences in uptake by including dummies for survey time quarter, calendar year and state/territory. Variable definitions and summary statistics are provided in Appendix Table A3.

care use of their young children (Almond & Currie 2011). We are particularly interested in finding out whether eligible children who take up the benefits are needier or whether they simply face lower informational or other barriers (Currie 2006). To investigate the former, in addition to some of the above-described variables capturing the disadvantageous children, we introduce lags of four measures representing the child's oral health conditions to the list of $Y_{i,t-1}$. We also have data on the reported frequency of the child's tooth-brushing, which is known to be an effective preventive oral health behaviour (Kumar *et al.* 2016). To see whether this behaviour affects the decision to access the public dental benefits, we include a variable describing whether a child was reported to have brushed his or her teeth twice a day in $Y_{i,t-1}$. We also include lags of household income (measured in 2014 price and included in logs) and private health insurance status in $Y_{i,t-1}$ as they may provide with substitutable financial resources to pay for children's dental care (Gnanamanickam *et al.* 2018).

To examine the possible role of informational barriers, we include some socio-demographic variables that are usually used as proxies for information and process costs in uptake studies such as household composition and educational level, presuming that single-parent households and low-skilled parents face higher costs (Currie & Grogger 2002). We also include a variable that indicates whether the child lived in accommodation owned by the family (hereinafter "owned home"), as opposed to living in rental accommodation, in $Y_{i,t-1}$. It has been hypothesised previously that children who live in an owned home may face lower information costs (Chareyron & Domingues 2018) due to the fact that their parents are more likely to receive the eligibility notification mail-out than those parents who reside in rental accommodation. For these programs, eligible households were mostly notified of their eligibility for the program by standard mail (DoH 2016).

We also include in $Y_{i,t-1}$ two variables that potentially represent cognitive biases and behavioural barriers to uptake of the benefits, as identified in the recent literature (Van Mechelen & Janssens 2017). This strand of literature highlights the importance of cognitive biases and behavioural barriers both to decide optimally and to act optimally. In our setting, parents of eligible children may be prevented from taking up the benefits for their children, for instance, because their appreciation of the benefits the programs offer may be impaired (Duflo *et al.* 2011; Mani *et al.* 2013). To model this potential cognitive barrier to uptake, we include a variable that indicates if the mother suffers from depression as a potential indicator (or driver) of cognitive bias. This variable exhibits some overlap with some of the other variables discussed above in the context of information processing costs.[12] The second variable included in $Y_{i,t-1}$ to capture potential behavioural barriers is the mother's smoking status. Smokers are usually assumed to have higher discount rates than non-smokers, in line with evidence of a positive association between smoking and high discount rates (Barlow *et al.* 2017). In this study context, smokers may discount the benefits of the public programs more heavily than non-smokers (O'Donoghue & Rabin 1999; Bertrand *et al.* 2006; Thaler & Sunstein 2008; Duflo *et al.* 2011) and hence be less likely to claim the available benefits for their children.

Finally, we explore whether the supply side of dental services markets affects children's access to dental benefits (Rossin-Slater 2013; Buchmueller *et al.* 2016) by including a variable that measures the density of dental practitioners registered at the local government area level in $Y_{i,t-1}$. It should be noted that all variables in the extended list $Y_{i,t-1}$ are measured before the uptake of the benefits to mitigate a concern that access to the benefits may influence such variables.

We estimate equation (1) separately for each of the two dental benefit programs because previous studies show that benefit levels and frequency of entitlement are important drivers of uptake (Blundell *et al.* 1988; Anderson & Meyer 1997; Tempelman & Houkes-Hommes 2016). For each program, we pool the data from all available calendar years to increase the sample size.[13] We measure uptake by the amount of benefit paid per calendar year (i.e., A$, measured in 2014 price). Since access to the MTDP is restricted to one dental occasion of service per year and our analysis in Section 3.2 shows that the amount paid is usually the same as the annual cap, we also measure uptake in terms of whether the child received any dental benefit during the year. We specify an Ordinary Least Squared (OLS) equation for ease of estimation and interpretation for the monetised benefit outcome and a probit model for the binary outcome.[14]

[12] Van Mechelen & Janssens (2017) note that while the traditional uptake model mainly focuses on the informational barriers related to finding out whether individuals are eligible, the more recent theoretical strand (mostly from behavioural economics) points to the obstacles in understanding and choosing among various options available. In our setting, the eligibility for child dental benefits is automatic and this reduces the role of finding the necessary information for individuals to become aware of their eligibility. Thus, maternal depression may impede uptake via the parent's impaired ability to understand and claim the available benefits for their children.

[13] Nevertheless, we experimented with estimating equation (1) by calendar year. Estimates (reported in Appendix Table B3) while lacking statistical power due to the small sample size are usually in line with the pooled results (reported in Table 3).

[14] Using a Tobit or hurdle model which accommodates the mass-of-zeros in the uptake decision leads to very similar findings. Likewise, applying a Poisson regression model to the annual number of access to CDBS where each eligible child can have more than one dental service paid by the scheme per year results in the same

## 5. Empirical results

### *5.1. Descriptive statistics*

Table 2 reports summary statistics by program and uptake status among eligible children. It suggests some statistical differences in the explanatory variables by uptake status and also, for a few variables, by program. Overall, as compared to non-takers of the benefits, takers appear to come from families from higher socio-economic backgrounds. Specifically, households who take up the benefits are more likely to have mothers with higher qualifications (MTDP only) or mothers with better mental health or less risky lifestyles, as proxied by smoking status. They are also more likely to come from two-parent households, to live in their own home, or to have private health insurance (MTDP only). Furthermore, takers are more likely to be breastfed at early childhood or have teeth brushed (or brush teeth) more frequently. We also find evidence of lower uptake by households where the child is identified as indigenous. One exception to these findings is that takers of CDBS are more likely, *ceteris paribus*, to come from lower-income households. Table 2 also reveals that takers tend to be older in MTDP while the opposite appears to be true in CDBS. However, there are no remarkable differences in other variables, including the child's birthweight and previous dental health conditions, by uptake status.

[Insert Table 2 here]

### *5.2. Regression results*

The regression results for our main variables using model (1) are presented in Table 3.[15] The results show that the child's previous oral health conditions do not drive the decision to take

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conclusions. For CDBS, we also experimented with measuring the outcomes over two consecutive calendar years (i.e., 2014-15 and 2015-16) and found similar results (See Appendix Table B3, Columns 7 and 8). We do not apply a Fixed Effects (FE) regression model to equation (1) for three reasons. First, as discussed in Section 3.2, uptake is measured annually while other variables, including eligibility, are recorded biennially, leading to little variation in the control variables during this relatively short study period. Second, FE regressions require that each child who is eligible for child dental benefits appears in the data on at least two occasions to be included in the regressions. This sample restriction, coupled with the fact that the child's eligibility changes over time, reduces the sample size significantly. Third, some potentially interesting variables are fixed over time because of their nature (e.g., Aboriginal status) or data availability (e.g., private health insurance status was only asked in the first wave of LSAC) so they are dropped in the FE regressions. Indeed, unreported FE regression results indicate little statistical power of all explanatory variables, probably due to the issues of insufficient variations in included variables, the small sample size or both. We also experimented with applying a Random Effects (RE) model to equation (1) and found results similar to those reported in Table 3. Results from these experiments are available upon request.

[15] Appendix Table B2 reports the estimation results when each variable in the extended control list is added individually. The results are largely similar to the results when all of the extended variables are introduced at the same time (rereported in Column 10 of Appendix Table B2). The similarity in the results suggests that each

up the benefits because the estimates of all included child dental health variables are statistically insignificant in all specifications (i.e., OLS and probit) for both programs. By contrast, Table 3 indicates that eligible children with better prior preventive oral health behaviours are statistically significantly more likely to take up the benefits and, on average, take up more. This pattern holds in all regressions with the OLS regression for CDBS as an exception where the parameter estimate on toothbrushing frequency is still positive but statistically insignificant. The pooled regression results from two programs (reported in Columns 5 and 6) indicate that, as compared to children who brushed their teeth less than twice per day, children who brushed teeth more often on average take up approximately A$6 more benefits or are 3 percentage points (or 12%)[16] more likely to access the benefits.

[Insert Table 3 here]

The estimates of family income and private health insurance status variables are negative in all regressions and are statistically significant (at least at the 10% level) for the CDBS and pooled regressions of both programs, presumably because these constitute financial substitutes for the eligible children. Specifically, the estimates of family income in CBDS (Columns 3 and 4) indicate that if family income increases by 1%, the access to child dental benefit decreases by 6.4 cents, or 0.03 percentage points. Similarly, relative to children from families without private health insurance, those with private health insurance take up A$10 less from CDBS or are less likely to take up by 3 percentage points (or 10%).[17] The negative correlation between income or private health insurance and uptake suggests that those with greater economic need do take up more intended benefits. Consistent with the wider literature on income/benefit effects in welfare participation, we refer to this negative relationship as evidence of welfare stigma in the uptake of the two child dental benefit programs (Friedrichsen *et al.* 2018).[18] Our finding of a negative impact of household income on the take-up of public child dental benefits in Australia is in line with evidence of a negative association between income and uptake of other public programs such as Housing Benefit in the UK (Blundell *et al.* 1988) and the Head

variable in the extended control list has a separate impact on the uptake. Appendix Table B2 also reveals that the estimates of variables in the basic list show little variations when the extended list is included, indicating that the extended variables have different effects from those in the basic list.

[16] = (3.27/28.4)*100; where 3.27 is the estimated coefficient on the child toothbrushing frequency variable (reported in Column 6 – Table 3) and 28.4 is the average uptake rate (reported in Table 1).

[17] Unfortunately, the dataset does not contain information on children's dental services that were paid from sources other than the public dental benefits for us to explore other related issues. For instance, we cannot investigate whether or not eligible children substitute privately-funded for publicly-funded oral care.

[18] In non-experimental studies, welfare stigma is typically analysed by testing for a positive correlation between benefit size and the probability of welfare uptake (Blundell *et al.* 1988; Blank & Ruggles 1996).

Start program in the US (Currie & Thomas 1995) or National School Lunch program in the US (Hoynes & Schanzenbach 2016).

Turning to estimates on the home ownership variable, we consistently find that children living in their own home statistically significantly (at the 1% level) take up more dental benefits and this pattern holds for both programs. Specifically, the pooled regression results of two programs (Columns 5 and 6) show that, as compared to eligible children living in a rented home, those living in an owned home take up A$12 more or are 5 percentage points (or 19%) more likely to take up the benefits. The positive impact of home ownership on uptake is in line with the idea that children in more stable housing are more likely to receive the (mailed) eligibility notification. If this is the case, this finding is consistent with a common finding about the role of the lack of information in non-uptake (Bhargava & Manoli 2015; Finkelstein & Notowidigdo 2019). An alternative interpretation is that homeowners may have better local knowledge, including information about local dental practitioners, so they take up more benefits.[19] It is also possible that renters and owners are different in other characteristics (some of which are already controls in the regression specifications) that also influence uptake decisions.

Estimates on the two variables that are invoked to capture cognitive biases and behavioural barriers to uptake are highly statistically significant and have expected signs. In particular, the estimates of maternal depression are negative in all regressions and statistically significant at the 5% level in MTDP and pooled regressions, suggesting that mothers with depression are less likely to claim the benefits for their children. In terms of the magnitude, the pooled regression results (Columns 5 and 6) show that, as compared to children of mentally healthy mothers, children with mentally-ill mothers access A$7 less or are 2.5 percentage points (or 9%) less likely to claim the benefits. Likewise, children of smoking mothers statistically significantly (at least at the 10% level) take up less benefits than children of non-smoking mothers. For instance, the pooled regression results indicate that the former takes up A$12 less or are 8 percentage points (or 27%) less likely to take up the benefits.

Our finding of the negative impact of maternal depression on uptake is in line with experimental evidence that individuals with mental health issues do not make the choice that

[19] We experimented with including a variable describing the mother's knowledge of local services, constructed from responses to the question "How strongly do you agree or disagree that if you need information about local services, you know where to find that information", in the regressions. Unreported estimates of this variable are not statistically significant at any conventional level, suggesting that available data do not seem to support this conjecture. Other available variables such as whether there is internet at home (only available in waves 5-7, and almost all families have internet at home) or whether there is computer at home (in the first 4 waves only) are also relatively uninformative in modelling the uptake behaviours.

is (expected, or assumed, to be) in their best private interest (Kung *et al.* 2018; Bayer *et al.* 2019). Similarly, the finding that smoking mothers fail to claim the benefits for their children is consistent with evidence that children of smoking mothers usually have poorer development outcomes (Mund *et al.* 2013). Taken together, the findings of the negative impact of maternal depression and risky lifestyles on uptake in this study are also in line with evidence of the intergenerational transmission of disadvantages documented in the literature (Black & Devereux 2011; Le & Nguyen 2018). To the best of our knowledge, these findings are novel to the uptake literature (Currie 2006; Finkelstein & Notowidigdo 2019).

Table 3 also indicates that the availability of local dental services does not affect uptake because estimates on the dental practitioner density variable, while positive in all regressions, are not statistically significant at any conventional level.[20] Likewise, regression results for remaining variables (reported in Appendix Table B1) suggest that other characteristics of the child and the mother generally do not influence uptake. There are two exceptions. First, uptake is increasing in child age (measured in months), albeit at a decreasing rate.[21] Second, while there is no statistical difference in the probability of uptake by the indigenous status, children with an Aboriginal background claim less benefits (for instance, by A$14 as in the pooled OLS regression (Column 5)), than non-indigenous children. We also observe that children who live in areas where there is a greater prevalence of reporting Aboriginal background take up less benefits, especially from CDBS, raising the possibility that social network effects may also be important for indigenous children.[22] Finally, estimates of some temporal and geographical variables are highly statistically significant, validating their inclusion as controls in the regressions.

The above results reveal some differences in the estimates by programs, suggesting that differential program designs may have some distinct influences on uptake, as found in the

[20] The estimate on the dental practitioner density variable is only statistically significant at the 5% level in the first year when LSAC K-cohort children became eligible to the MTDP (i.e., 2011) in regressions by year (See Appendix Table B3).

[21] This is because the estimate of age is positive and statistically significant while the estimate of age squared is negative and statistically significant. Appendix Table B3 additionally shows that the impact of the child's age is only observed in 2011 when LSAC K-cohort children became eligible for the MTPD for the first time.

[22] Motivated by Mullainathan *et al.* (2000), we include an interaction term between the child's Aboriginal background and the ratio of individuals with an Aboriginal background living within the child's local area, identified at a Statistical Area (SA) 2 level, in the uptake equation. Unreported estimates of the interaction term are negative and statistically significant (at least at the 5% level and in the probit regressions only), suggesting a compounding effect of these two variables. It is interesting to note that this finding still holds when we control for other local variables, including the supply of dental practitioners, in the regressions. These results suggest a potential role of social networks in uptake of public benefits, as proposed by Mullainathan *et al.* (2000).

literature (Currie 2006). For instance, household income and private health insurance appear to have more pronounced effects in terms of the statistical level and magnitude on uptake of CDBS than MTDP. By contrast, the impacts of maternal depression and smoking status are more noticeable for MTDP than CDBS. However, we find little apparent differences in the estimates of other variables, including the child dental health conditions, child preventive oral health behaviours and home ownership status, by programs.[23] As the sign of almost all estimates is consistently similar for both programs, in what follows, in the interest of parsimony and in order to improve the statistical power of the estimates, we will focus on the results from pooled regressions on the two programs. Similarly, because the directional impacts of all variables are largely the same in two specifications (i.e., OLS and probit) and the binary measure of uptake is relatively more informative than the continuous monetary measure, we will use the former for the rest of the paper.

## 6. Robustness checks

### *6.1. Sample selection issue*

Above we explored the drivers of uptake among a sample of potentially eligible individuals, as has been done in most non-experimental studies in the uptake literature (Currie 2006; Van Mechelen & Janssens 2017). Our dataset contains sufficient information (such as the child's ages and family ISH) to allow us to identify eligible children accurately. Nevertheless, there is still the concern that some unobservable factors may be correlated with both the probability of reporting that the family received any type of relevant government payment and the uptake of the benefits. If this were the case, the parameter estimates on some of the explanatory variables in the uptake equation will be biased and inconsistent (Wooldridge 2010). In the main analyses, to deal with such concerns, we relied on the richness of the data to control for a comprehensive list of explanatory variables, including some variables that are typically used to determine the family's eligibility to the government support payments such as family income and household structure variables. We also exploited the panel nature of the data to introduce lags of time-variant variables in the regression to address such a threat.

In this section, we invoke a sample selection correction model to account for the possible endogenous sample selection. In particular, in the spirit of a Heckman sample selection correction model (Heckman 1979), we specify an auxiliary model which predicts the likelihood that the child is eligible for the child dental benefit using a probit model on a sample of all

[23] Unfortunately, available data do not allow us to more definitively infer which program better facilitates uptake.

children. We then estimate this auxiliary model simultaneously with a uptake equation, similar to equation (1), using a sample of eligible children, allowing for the potential correlation in error terms of the two equations (Wooldridge 2010). One challenge to this approach is to find (at least) one exclusion restriction variable to identify the selection equation. This variable must satisfy the following conditions: (i) it must be sufficiently correlated with the probability that the child is eligible for the benefits, (ii) it must be uncorrelated with the uptake $A_{i,t}$ except through the probability that the child is eligible for the benefits, and (iii) it cannot be correlated with the error term in the uptake equation.

We propose to use a variable describing income cut-offs over which a family is not eligible for the FTB A as an exclusion restriction variable. This variable is likely to satisfy the three requirements specified above. Specifically, our data show that among all children identified as eligible for child dental benefits, almost all (93%) of them were eligible because their family received FTB A at the time of survey. In turn, eligibility for FTB A is exclusively determined by the family income and the number of dependent children at different age groups (see Appendix Table A4 for an example of income limits for FTB A). Our dataset contains information that allows us to construct a variable to capture the yearly income cut-offs that vary over time and between families of different sizes. Thus, by design of the FTB A and two child dental benefit programs (DoHS 2019), this variable will determine whether a child is eligible for the child dental benefits. Furthermore, we will also control for family income and the number of children at different ages in both equations (i.e., the selection and uptake). This variable is theoretically attractive because it should directly affect the child's eligibility, but only indirectly affect their uptake of the benefits (via their eligibility). We will empirically strengthen the validity of the exclusion restriction variable against the third requirement by (i) controlling for a rich list of variables which are potentially associated with our exclusion restriction variable, and (ii) introducing lags of all variables in the extended list as described in Section 4.[24]

[Insert Table 4 here]

[24] Theoretically, we can exploit an age-based eligibility rule identified by the differences in children's ages and the timing of the policies as a potential source to identity the selection equation. This approach requires that observed children became eligible for the benefit because of their ages at different survey times. However, almost all children from the same cohort (i.e., B or K) in our data became eligible due to their ages at the same time (see Appendix Table A1), making this approach impractical. Our approach to use income cut-offs as a source of identification is similar to a regression discontinuity design (Lee & Lemieux 2010).

Estimates from the sample selection correction model are reported in Table 4 – Column 2. The correlation between the errors from the uptake equation and the errors from the selection equation (reported at the bottom of Column 2) is -0.49 and statistically significant at the 1% level, indicating that selection in the sample is endogenous. This negative correlation estimate further suggests that unobservable factors that increase the probability of being eligible for the benefits tend to occur with the unobservable factors that decrease the chance of uptake. We also observe that estimates of income turn from negative and statistically significant in the baseline regression (rereported in Column 1) to positive and statistically insignificant in the selection-adjusted regression. This noticeable change in the estimate of income is consistent with the negative error correlation estimate and the design of the government welfare programs where income is normally the dominant means-test criterion. By contrast, coefficient estimates for other variables retain their signs and levels of statistical significance. Moreover, the coefficient estimates on variables capturing child toothbrushing frequency, home ownership and maternal depression are even greater in the sample selection correction regression. For instance, the estimate of home ownership almost doubles in the sample selection correction regression as children living in owned homes are 10 percentage points more likely to uptake the benefits (as compared to 5 percentage points in the baseline regression).

The results of this robustness check suggest that eligible children from more socio-economic disadvantaged families, as measured by living in a rented home, having depressed or smoking mothers or brushing their teeth less often, tend to take up less the benefits. Additional results from the eligibility determinant equation (reported in Appendix Table B4) show that these children are also more likely to be targeted by the two child dental benefit programs.[25] Specifically, the results indicate that children living in rented homes, having depressed mothers and brushing their teeth less frequently have a much higher probability of being eligible for the benefits. Taken collectively, the results suggest that these two programs may not reach some of the selected groups who need them most.

[25] Other results from the eligibility determinant regression in Appendix Table B4 are as expected. For instance, consistent with the design of both child dental programs, children from more socio-economically disadvantaged families, as measured by having mothers with lower qualifications or more children, living in a single parent family, having lower household income or no private health insurance, are more likely to be eligible. Furthermore, while children with prior cavities have a higher chance of being eligible for the benefits, the opposite is true for children having teeth filled due to decay in two years before the survey time. Finally, and importantly, the estimate of the income cut-offs is positive and highly statistically significant with a Chi-square test statistic for its significance is 960, alleviating weak instrument concerns.

### 6.2. *Different eligibility identification rules*

This section checks the sensitivity of the results against three alternative eligibility identification approaches. In particular, in cases when the LSAC survey was not undertaken in the uptake year we identify the child's eligibility in terms of means-test using the family's government payment records reported in the year following the uptake year (denoted Eligibility Rule 2, see Appendix Table A2 for details). Alternatively, in such cases, we define the child as eligible for the benefits in terms of means-test if their family received any relevant government payment in the year either before or after the uptake year, denoted as Eligibility Rule 3. We still use the family's ISH recorded at the same year of uptake when the LSAC survey was implemented in the uptake year, as was done in the baseline analysis using Eligibility Rule 1. Finally, we include children who were identified as "ineligible" for the benefits using Eligibility Rule 1 but have any access to the benefits in the uptake regression (1). Results from these experiments (reported in Columns 3, 4 and 5 of Table 4) generally produce estimates on the main variables that are similar to the baseline results. An exception is the estimated coefficient on income: while it is negative, as in the baseline regression, it is no longer statistically significant when we include "ineligible" children in the regressions (Column 5).

### 6.3. *Use administrative data to identify eligibility*

We next check the robustness of the results using more objective and more frequent information obtained from linked administrative data sources to identify the child's eligibility. Our dataset contains administrative historical government payment records for a subset of K-cohort children that we use to identify their eligibility in terms of the means-test.[26] Appendix Table B5 summarises the eligibility and uptake of the dental benefits for these children. It shows that 61% of them were identified as eligible for the benefits during the 2011-15 period. This eligibility rate is substantially higher than an eligibility rate of just 45% using self-reported ISH for the same children during the same time horizon (results are reported in Appendix Table B6). The difference in eligibility rates using administrative and self-reported data sources documented in this study is consistent with the oft-observed pattern of individuals under-

[26] Specifically, we have necessary information for 2,807 K-cohort children who gave consent to have their administrative family ISH to be linked to LSAC data in Wave 7. Administrative ISH (from Centrelink) were successfully linked to LSAC data for 2,191 children (or 78 % of all consented children). For them, we have ISH from FY 2003-04 (i.e., when they were born) up to FY 2014-15 (the most recent FY when financial tax benefit entitlements and eligibility have been reconsolidated). The most common reason for why the remaining 22 % children were not linked to Centrelink data is because their families did not receive any type of government support during the whole period from 2003 to 2015 (AIFS 2018). They are therefore identified as ineligible for dental benefits in this study.

reporting their welfare receipts in surveys (Meyer *et al.* 2015). However, this is the only noticeable difference that we observe using more objective and more frequent data. Appendix Table B5 shows no apparent difference in other summary statistics using two different data sources. Likewise, regression results (reported in Column 6 of Table 4) show little sensitivity in the main findings.

### *6.4. Different control variables*

Finally, we experiment with including different control variables in the uptake equation (1).[27] Appendix Table B7 indicates that using maternal K6 as an alternative measure for maternal depression status produces the same results. Furthermore, we experiment with employing the maternal frequent binge drinking status as a proxy for maternal discount factor and find the parameter estimate to be statistically insignificant estimate, perhaps because drinking status does not indicate the latent "risky lifestyle" as well as does smoking status in this sample. We also include similar variables capturing behavioral barriers potentially originating from the child's father such as the paternal depression and smoking or drinking status in the uptake equation and find that their parameter estimates are statistically insignificant (see Appendix Table B7).[28] The differential estimates between maternal and paternal variables suggest a more important role of mothers in the decision to take up the benefits for children, a finding which is in line with other literature on the topic (Brown & van der Pol 2015; Nguyen *et al.* 2019).

In the baseline regressions, we distinguished four child oral health problems because, while they are highly correlated, each of them may capture different aspects of oral health and hence the demand for subsequent dental care.[29] In this section, we use a dummy variable indicating if the child had any of the four oral health problems listed above and find its estimate to be statistically insignificant. The results also produce a statistically insignificant estimate when we replace all four variables measuring the child dental health conditions by a variable describing whether the child had no treatment when they were reported to have dental decay (this variable is only available in waves 5 to 7). We also experiment with other slightly different child dental health conditions reported by the child (these questions were asked to K-cohort

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[27] In the results reported in this section, each of additional variables was added to the specification sequentially, one-by-one. Other variables in the extended list $Y_{i,t-1}$ are not included to get a separate impact of each of these additional variables.

[28] While we did not find evidence that paternal depression or smoking influenced uptake, we note that some caution is warranted in the interpretation of these results because paternal information is more sparse than maternal information in the LSAC and this could affect our power to detect the influence of fathers on uptake.

[29] For example, a child with dental decay may have higher demand for dental care services in the future. By contrast, if a child had teeth pulled in the last 2 years, this may conceivably reduce the subsequent demand for dental care.

children in waves 6 and 7 only) and find that children with tooth pain are more likely (by about 3 percentage points) to take up the offered public benefits. However, we find no statistically significant effects of other child oral health conditions, including dark teeth, gum pain or having blood on the toothbrush after brushing teeth, on uptake.

## 7. Discussion and conclusion

In this paper we use linked survey and administrative data with accurate information on eligibility and uptake to understand why less than a third of all eligible families actually claim public dental benefits for their children. We provide new evidence consistent with the ideas of cognitive biases and behavioural barriers to uptake as projected by the recent strand of uptake literature. In addition, we find that such barriers appear mainly to originate from maternal characteristics. Specifically, the results show that mothers with depression are 2.5 percentage points (or 9%) less likely to claim the benefits for their children. Similarly, smoking mothers are 8 percentage points (or 27%) less likely to take up the benefits. Consistent with the evidence of behavioural barriers to uptake, the results also demonstrate that while prior preventive oral health behaviours affect the subsequent uptake, the child's previous dental health conditions do not.

We also find some evidence that is in line with the predictions of the conventional economic approach. In particular, we find some suggestive evidence that the lack of information may be an important factor behind this low uptake as children living in owned homes are 5 percentage points (or 19%) more likely to take up the benefits than children in rented homes. Furthermore, the results are consistent with the evidence of welfare stigma in uptake of the two child dental benefit programs as eligible children from families with higher incomes or private health insurance exhibit lower benefits uptake. While the foregoing results are robust to various tests, the indicative evidence of welfare stigma does not hold when we address the possible endogenous sample selection using a Heckman selection correction model.

Our findings of factors shaping the uptake decision have some potentially important policy implications. For example, to the extent that policymakers view raising uptake as a policy objective, the results provide insight into which groups policies that aim to help disadvantaged children should target. Furthermore, low uptake, particularly among children from more disadvantaged backgrounds, would reflect a failure of policies to deliver benefits to those who most need them (Bhargava & Manoli 2015). Therefore, policies to improve uptake among disadvantaged groups may be more effective if additional strategies were adopted to influence these population sub-groups. While some of barriers identified in this paper, including cognitive biases and behavioural barriers, may not be easily overcome, several studies have shown it may be feasible to address them. For instance, the role of limited cognitive ability in non-uptake can be mitigated by reminders about eligibility (Altmann & Traxler 2014; Karlan *et al.* 2016; Finkelstein & Notowidigdo 2019) or simplification, e.g., through a visually more appealing notice (Bertrand *et al.* 2010; Bhargava & Manoli 2015). Reducing such barriers to uptake among disadvantaged groups may also help to lessen the documented intergenerational transmission of disadvantages (Black & Devereux 2011). Overall, the results thus produce insights into the operation of the programs that are relevant not only to the success of the current program, but also for policy initiatives to improve their uptake in a range of population sub-groups.

This study discovered some new factors driving the low up-take of public benefit programs. However, due to the nature of the data and method employed, it remains unclear whether providing more information in the form of a reminder about eligibility or simplification would improve uptake, particularly among disadvantaged groups. To this end, more research, such as the random experiments as have been employed recently in this literature (Bhargava & Manoli 2015; Finkelstein & Notowidigdo 2019), is needed to establish the effectiveness of such interventions or identify other barriers to program participation. Furthermore, as the main aim of two public dental programs is ultimately to improve the dental health of children, further study of the impact of access-improving initiatives on child dental health itself is a topic that also deserves further research.

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Table 1: Eligibility and uptake of child dental benefits for LSAC children over time

| | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2011-16 |
|---|---|---|---|---|---|---|---|
| | | MTDP | | | CDBS | | |
| Eligible (%) | 48.4 | 42.3 | 42.3 | 40.7 | 40.7 | 35.6 | 40.8 |
| Uptake rate (% among eligible) | 21.0 | 28.8 | 22.7 | 31.3 | 30.5 | 31.4 | 28.4 |
| Mean of benefit claimed per visit (A$, conditional on uptake) | 154.7 | 158.5 | 161.4 | 275.7 | 259.2 | 269.5 | 233.9 |
| Standard deviation of benefit per visit (A$, conditional on uptake) | 19.4 | 18.6 | 19.9 | 188.1 | 162.6 | 167.8 | 153.2 |
| Had to pay out of pocket (%, conditional on uptake) | 0.0 | 0.0 | 2.4 | 6.4 | 4.3 | 4.4 | 3.7 |
| Number of dental visits per year (conditional on uptake) | 1.0 | 1.0 | 1.0 | 1.8 | 1.7 | 1.7 | 1.5 |

Notes: Figures are adjusted for sampling weights. Eligibility Rule 1 (see Appendix Table A2 for details) is used.

Table 2: Summary statistics by programs and uptake status among eligible children

| | MTDP | | | CDBS | | |
|---|---|---|---|---|---|---|
| | Uptake | Non-uptake | (1) - (2) | Uptake | Non-uptake | (4) - (5) |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| Child age (months) | 146.86 | 145.15 | 1.71*** | 157.94 | 160.13 | -2.2*** |
| Male | 0.51 | 0.54 | -0.03* | 0.52 | 0.53 | -0.01 |
| Australian-born | 0.96 | 0.97 | -0.01 | 0.98 | 0.99 | -0.01 |
| Aboriginal | 0.03 | 0.05 | -0.02*** | 0.03 | 0.05 | -0.01** |
| Low birthweight | 0.08 | 0.09 | -0.01 | 0.08 | 0.08 | 0.00 |
| Breastfed at early childhood | 0.72 | 0.66 | 0.06*** | 0.69 | 0.65 | 0.04*** |
| Mother's age (years) | 41.93 | 40.74 | 1.19*** | 42.22 | 42.19 | 0.03 |
| Mother NESB migrant | 0.26 | 0.24 | 0.02 | 0.27 | 0.21 | 0.06*** |
| Mother ESB migrant | 0.13 | 0.11 | 0.02* | 0.11 | 0.15 | -0.03*** |
| Mother with certificate | 0.51 | 0.51 | 0.00 | 0.57 | 0.59 | -0.02 |
| Mother with bachelor degree | 0.20 | 0.16 | 0.03** | 0.20 | 0.19 | 0.01 |
| Number of siblings | 1.85 | 1.92 | -0.07 | 1.89 | 1.81 | 0.08* |
| Lived with both parents | 0.64 | 0.57 | 0.07*** | 0.59 | 0.55 | 0.04*** |
| Child had cavities | 0.25 | 0.26 | -0.01 | 0.26 | 0.26 | 0.00 |
| Child had teeth filled due to decay | 0.21 | 0.21 | 0.00 | 0.22 | 0.21 | 0.01 |
| Child had teeth pulled due to decay | 0.02 | 0.03 | -0.01* | 0.05 | 0.05 | 0.00 |
| Child had accidental tooth damage | 0.04 | 0.05 | -0.01 | 0.03 | 0.03 | 0.00 |
| Child brushed teeth twice | 0.63 | 0.57 | 0.06*** | 0.61 | 0.58 | 0.04** |
| Household yearly income (A$1,000) | 78.29 | 76.51 | 1.78 | 75.08 | 81.77 | -6.69*** |
| Had private health insurance | 0.33 | 0.27 | 0.06*** | 0.29 | 0.29 | 0.00 |
| Lived in an owned home | 0.72 | 0.59 | 0.13*** | 0.65 | 0.59 | 0.06*** |
| Mother had depression | 0.35 | 0.43 | -0.08*** | 0.37 | 0.40 | -0.03** |
| Mother smoked cigarette | 0.17 | 0.30 | -0.13*** | 0.20 | 0.26 | -0.06*** |
| Dental practitioner density | 0.81 | 0.79 | 0.02 | 0.94 | 0.84 | 0.09* |
| Number of observations | 1077 | 2974 | | 1942 | 3965 | |

Notes: Figures are sample means and adjusted for sampling weights. Estimated sample from the regression of the child dental benefit on a set of explanatory variables as described in the text. Tests are performed on the significance of the difference between the sample mean for female and male students. The symbol *denotes significance at the 10% level, **at the 5% level, and ***at the 1% level.

Table 3: Determinants of uptake among eligible children – Main results

| Variables | MTDP | | CDBS | | MTDP and CDBS | |
|---|---|---|---|---|---|---|
| | OLS | Probit | OLS | Probit | OLS | Probit |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Child had cavities | 5.78 | 2.49 | 13.16 | -1.76 | 8.45 | -0.52 |
| | [7.05] | [4.22] | [12.07] | [3.22] | [8.29] | [2.68] |
| Child had teeth filled due to decay | -6.42 | -2.78 | 10.63 | 3.96 | 4.86 | 1.67 |
| | [7.26] | [4.36] | [12.06] | [3.24] | [8.45] | [2.73] |
| Child had teeth pulled due to decay | -14.56 | -7.78 | -7.81 | 0.67 | -5.83 | -0.48 |
| | [9.60] | [6.38] | [11.85] | [3.25] | [9.41] | [2.90] |
| Child had accidental tooth damage | -0.84 | -0.03 | 2.87 | 0.24 | 0.85 | -0.36 |
| | [5.79] | [3.64] | [12.43] | [3.94] | [7.17] | [2.89] |
| Child brushed teeth twice | 5.45** | 3.53** | 5.83 | 3.07** | 5.70** | 3.27*** |
| | [2.59] | [1.56] | [4.36] | [1.39] | [2.86] | [1.09] |
| Household income (log) | -1.62 | -0.87 | -6.24* | -3.24*** | -4.52* | -2.31*** |
| | [2.16] | [1.22] | [3.19] | [0.96] | [2.35] | [0.77] |
| Had private health insurance | -3.35 | -1.10 | -10.48** | -2.97* | -7.87** | -2.13 |
| | [3.45] | [1.95] | [4.98] | [1.65] | [3.47] | [1.35] |
| Lived in an owned home | 9.28*** | 5.64*** | 13.31*** | 5.06*** | 11.68*** | 5.32*** |
| | [3.01] | [1.86] | [4.94] | [1.60] | [3.31] | [1.28] |
| Mother had depression | -6.61** | -3.49** | -6.15 | -1.73 | -6.52** | -2.49** |
| | [2.71] | [1.64] | [4.34] | [1.41] | [2.90] | [1.13] |
| Mother smoked | -14.79*** | -9.99*** | -10.17* | -5.53*** | -12.31*** | -7.57*** |
| | [3.16] | [2.13] | [5.48] | [1.81] | [3.60] | [1.46] |
| Dental practitioner density | 1.29 | 0.80 | 0.31 | 0.91 | 0.71 | 0.94 |
| | [2.76] | [1.39] | [2.54] | [0.70] | [2.17] | [0.63] |
| Observations | 4,051 | 4,051 | 5,907 | 5,907 | 9,958 | 9,958 |
| R2 (Pseudo R2 for probit) | 0.05 | 0.05 | 0.03 | 0.03 | 0.05 | 0.03 |

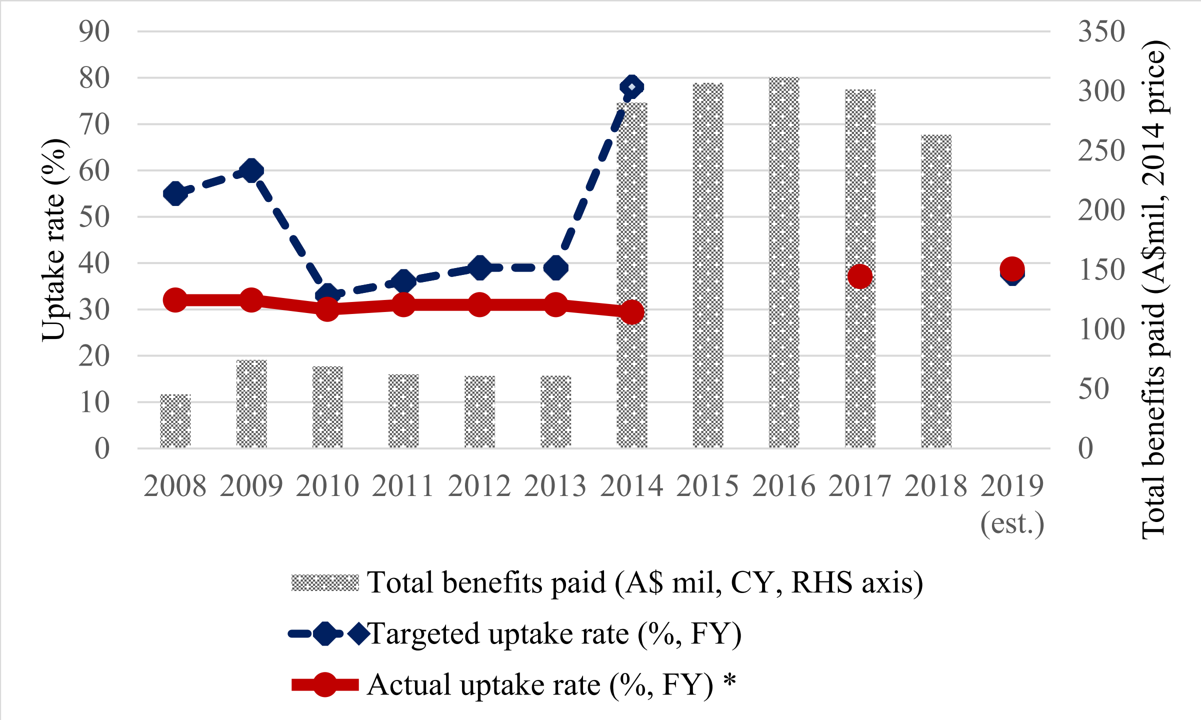
Notes: Results from OLS regressions for continuous outcomes and probit regressions for binary outcomes. Marginal effects (coefficient estimates and standard errors are multiplied by 100 for aesthetic purposes) are reported for probit regressions. Other explanatory variables include characteristics of the child, the mother and the household, local socio-economic background variables, state/territory dummies, survey year and quarter dummies (reported in Appendix Table B1). Robust standard errors clustered at the individual level in parentheses. The symbol *denotes significance at the 10% level, **at the 5% level, and ***at the 1% level.

Table 4: Robustness checks – Different model specifications and eligibility identifications

| Variables | Baseline | Sample selection | Eligibility Rule 2 | Eligibility Rule 3 | Include "ineligible" | Administrative data |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Child had cavities | -0.52 | -2.58 | -0.75 | -1.23 | -3.27 | 4.24 |
| | [2.68] | [2.85] | [2.91] | [2.63] | [2.76] | [4.70] |
| Child had teeth filled due to decay | 1.67 | 4.01 | 2.20 | 2.33 | 5.13* | -3.13 |
| | [2.73] | [2.91] | [2.99] | [2.68] | [2.82] | [4.85] |
| Child had teeth pulled due to decay | -0.48 | -0.06 | -0.55 | 0.33 | 0.99 | -0.96 |
| | [2.90] | [3.15] | [3.27] | [2.87] | [3.01] | [6.21] |
| Child had accidental tooth damage | -0.36 | -0.61 | 0.50 | 0.03 | -1.02 | -2.42 |
| | [2.89] | [3.04] | [3.19] | [2.79] | [2.82] | [3.91] |
| Child brushed teeth twice or more | 3.27*** | 4.41*** | 3.75*** | 3.22*** | 4.33*** | 3.29** |
| | [1.09] | [1.18] | [1.22] | [1.06] | [1.12] | [1.62] |
| Household income (log) | -2.31*** | 0.22 | -2.22*** | -2.16*** | -0.62 | -1.00 |
| | [0.77] | [0.89] | [0.79] | [0.71] | [0.72] | [0.91] |
| Had private health insurance | -2.13 | 1.36 | -1.66 | -2.43* | -0.63 | -1.47 |
| | [1.35] | [1.48] | [1.49] | [1.31] | [1.35] | [1.91] |
| Lived in an owned home | 5.32*** | 9.87*** | 5.06*** | 5.13*** | 8.20*** | 5.26*** |
| | [1.28] | [1.42] | [1.41] | [1.26] | [1.32] | [1.99] |
| Mother had depression | -2.49** | -4.56*** | -2.13* | -2.36** | -3.96*** | -2.15 |
| | [1.13] | [1.21] | [1.26] | [1.10] | [1.14] | [1.63] |
| Mother smoked | -7.57*** | -7.71*** | -7.07*** | -7.43*** | -7.66*** | -8.97*** |
| | [1.46] | [1.61] | [1.59] | [1.43] | [1.55] | [2.28] |
| Rho | | -0.49*** | | | | |
| | | [0.05] | | | | |
| Observations | 9,958 | 26,752 | 8,741 | 10,790 | 11,450 | 5,166 |

Notes: Results are from probit regressions for Columns 1, 4, 5, 6 and 7 and probit with sample selection correction regression for Column 2. Sample: pooled sample of both programs. Marginal effects (coefficient estimates and standard errors are multiplied by 100 for aesthetic purposes) are reported. Rho is the estimate of correlation in error terms. Other explanatory variables include characteristics of the child, the mother and the household (as described in the text), local dental practitioner density, local socio-economic background variables, state/territory dummies, year dummies, and survey quarter dummies. Robust standard errors clustered at the individual level in parentheses. The symbol *denotes significance at the 10% level, **at the 5% level, and ***at the 1% level.

Figure 1: The development of child dental benefit programs




Source: DoH (2016), Health Portfolio Budget Statements (various years for uptake rates) and Medicare Statistics at the Department of Human Services (for total benefit paid). CY indicates Calendar Year and FY refers to Financial Year.

## Appendices for online publication and review purposes

Appendix A: Data and policy descriptions

Appendix B: Additional results

Appendix Table A1: Timing of policies and ages of LSAC children

| LSAC wave | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| LSAC survey year | 2004 | 2006 | 2008 | 2010 | 2012 | 2014 | 2016 |
| Policies (eligible ages) | | | MTDP (12-17 years old) | | | CDBS (2-17 years old) | |
| B-cohort children (age, eligibility) | 0/1 | 2/3 | 4/5, not eligible | 6/7, not eligible | 8/9, not eligible | 10/11, eligible | 12/13, eligible |
| K-cohort children (age, eligibility) | 4/5 | 6/7 | 8/9, not eligible | 10/11, not eligible | 12/13, eligible | 14/15, eligible | 16/17, eligible |

Appendix Table A2: Matching rules between Medicare and LSAC data

| Calendar year of dental benefit uptake in Medicare | Means-test eligibility measures in LSAC wave (survey year) | Control variables measured in LSAC wave (survey year) |
|---|---|---|
| 2011 | Eligibility 1: Wave 4 (2010) | Wave 4 (2010) |
| | Eligibility 2: Wave 5 (2012) | |
| | Eligibility 3: Wave 4 (2010) and Wave 5 (2012) | |
| 2012 | Eligibility 1: Wave 5 (2012) | Wave 4 (2010) for variables in the extended list. Wave 5 (2012) for other variables. |
| | Eligibility 2: Wave 5 (2012) | |
| | Eligibility 3: Wave 5 (2012) | |
| 2013 | Eligibility 1: Wave 5 (2012) | Wave 5 (2012) |
| | Eligibility 2: Wave 6 (2012) | |
| | Eligibility 3: Wave 5 (2012) and Wave 6 (2014) | |
| 2014 | Eligibility 1: Wave 6 (2014) | Wave 5 (2012) for variables in the extended list. Wave 6 (2014) for other variables. |
| | Eligibility 2: Wave 6 (2014) | |
| | Eligibility 3: Wave 6 (2014) | |
| 2015 | Eligibility 1: Wave 6 (2014) | Wave 6 (2014) |
| | Eligibility 2: Wave 7 (2016) | |
| | Eligibility 3: Wave 6 (2014) and Wave 7 (2016) | |
| 2016 | Eligibility 1: Wave 7 (2016) | Wave 6 (2014) for variables in the extended list. Wave 7 (2016) for other variables. |
| | Eligibility 2: Wave 7 (2016) | |
| | Eligibility 3: Wave 7 (2016) | |

Appendix Table A3: Variable description and summary statistics

| Variable | Description | Mean | Min | Max |
|---|---|---|---|---|
| Child age | Child age in month | 152.29 | 120.00 | 216.00 |
| Male | Dummy variable: = 1 if the child is a male and zero otherwise | 0.53 | 0.00 | 1.00 |
| Australian-born | Dummy variable: = 1 if the child is born in Australia and zero otherwise | 0.98 | 0.00 | 1.00 |
| Aboriginal | Dummy variable: = 1 if the child has an Aboriginal and Torres Strait Islanders (ATSI) origin and zero otherwise | 0.04 | 0.00 | 1.00 |
| Low birthweight | Dummy variable: = 1 if the child birth weight is 2,500g or lower and zero otherwise | 0.07 | 0.00 | 1.00 |
| Breastfed at early childhood | Dummy variable: = 1 if the child was breastfed at 3 or 6 months of age and zero otherwise | 0.70 | 0.00 | 1.00 |
| Mother's age | Child's mother's age in year | 42.10 | 19.00 | 70.00 |
| Mother NESB migrant | Dummy: = 1 if mother was born in a Non-English Speaking Background (NESB) country and zero otherwise | 0.19 | 0.00 | 1.00 |
| Mother ESB migrant | Dummy: = 1 if mother was born in an English Speaking Background (ESB) country and zero otherwise | 0.14 | 0.00 | 1.00 |
| Mother with certificate | Dummy: = 1 if mother has a certificate and zero otherwise | 0.53 | 0.00 | 1.00 |
| Mother with bachelor degree | Dummy: = 1 if mother has a bachelor degree or higher and zero otherwise | 0.23 | 0.00 | 1.00 |
| Number of siblings | Number of siblings the child has | 1.82 | 0.00 | 10.00 |
| Lived with both parents | Dummy variable: = 1 if the child lived with both biological parents at the survey time and zero otherwise | 0.61 | 0.00 | 1.00 |
| Child had cavities | Dummy variable: = 1 if the child had cavities or dental decay in two years prior to the survey time and zero otherwise | 0.26 | 0.00 | 1.00 |
| Child had teeth filled due to decay | Dummy variable: = 1 if the child had teeth filled due to decay in two years prior to the survey time and zero otherwise | 0.21 | 0.00 | 1.00 |
| Child had teeth pulled due to decay | Dummy variable: = 1 if the child had cavities or dental decay in two years prior to the survey time and zero otherwise | 0.04 | 0.00 | 1.00 |
| Child had accidental tooth damage | Dummy variable: = 1 if the child had accidental tooth damage in two years prior to the survey time and zero otherwise | 0.04 | 0.00 | 1.00 |
| Child brushed teeth twice | Dummy variable: = 1 if the child brushed teeth (or have teeth brushed) twice or more a day and zero otherwise | 0.60 | 0.00 | 1.00 |
| Household yearly income | Yearly household income (=weekly household income X 52), A$1,000, measured in 2014 price | 82.06 | 0.00 | 1194.26 |
| Had private health insurance | Dummy variable: = 1 if the family had private health insurance and zero otherwise (only asked in Wave 1) | 0.34 | 0.00 | 1.00 |
| Lived in an owned home | Dummy variable: = 1 if the child lived in a home owned outright or being purchased and zero otherwise | 0.65 | 0.00 | 1.00 |
| Mother had depression | Dummy variable: = 1 if the mother was depressed for two weeks or more in the year prior to the survey time and zero otherwise | 0.38 | 0.00 | 1.00 |
| Mother smoked cigarette | Dummy variable: = 1 if the mother currently smokes cigarettes at the survey time and zero otherwise | 0.22 | 0.00 | 1.00 |
| Dental practitioner density | Ratio of registered dental practitioners (over 2013-16) per 1000 persons in the local government area | 0.83 | 0.00 | 19.38 |

Notes: Estimated sample from the pooled regression of uptake of two programs (N = 9,958).

Appendix Table A4: Example of income limits for Family Tax Benefit Part A between 20 March – 30 June 2012

| | No. children 18-21 years (excluding secondary students aged 18–19 years) | | | |
|---|---|---|---|---|
| No. children aged 0–17 yrs, or secondary students aged 18–19 years | Nil | One | Two | Three |
| Nil | | $102,870 | $115,219 | $128,553 |
| One | $101,312 | $113,661 | $126,996 | $140,331 |
| Two | $112,104 | $125,439 | $138,773 | $152,108 |
| Three | $123,881 | $137,216 | $150,551 | $163,885 |

Notes: This table shows the income limits at which Family Tax Benefit Part A, including the supplement, may not be paid (A$ per annum). Source: DoHS (2019).

Appendix Figure A1: 2012 MTDP voucher

Australian Government
Department of Human Services
medicare

# Medicare Teen Dental Plan
## Annual preventative dental check

**Your $163.05 teen dental voucher**

**This voucher is valid between 1 January and 31 December 2012**

This voucher entitles
to claim a dental benefit from Medicare for one preventative dental check this calendar year, as long as all eligibility requirements of the service are met. The service is described below.
Take this voucher and your Medicare card to your appointment.

### Who can provide the preventative dental check?

- Private dentists
- dentists in public dental clinics, including school-based clinics, and
- dental hygienists or dental therapists under supervision or oversight of a dentist.

### How do I use the voucher?

Using the voucher is easy—just make an appointment with a dentist.

When making a booking, ask:

- does the dentist accept the voucher
- will the voucher cover the full cost of the check, and
- will there be any extra costs?

**Claim for your preventative dental check**

After your preventative dental check the dentist will either:

- bulk bill the service by asking you to sign an assignment of benefit form with no cost to you
- ask you to pay in full up front—you then claim your benefit (up to $163.05) through Medicare, just like other Medicare benefits, or
- ask you to take your unpaid account to Medicare—you will then be sent a cheque to take back to the dentist.

If the dentist charges more than $163.05 for the preventive dental check, you'll need to pay the difference. Other dental treatment services are not covered by the voucher.

For more information go to **humanservices.gov.au**, call **132 011*** or visit your local Service Centre.
* Call charges apply

| Dental Benefits Schedule (DBS) item number | Description of eligible service | Maximum benefit payable by Medicare |
|---|---|---|
| 88000 | Preventative dental check | $163.05 |

8678.1201

## Voucher for a preventative dental check

$163.05

| Item number | Description | Maximum benefit | Expiry | Voucher number |
|---|---|---|---|---|
| | | | | |

Australian Government
Department of Human Services
medicare

Notes: Source: DoH (2016).

Appendix Figure A2: 2014 CDBS notification letter

Australian Government
Department of Health

If not delivered return to PO Box 1001
TUGGERANONG GREENWAY DC ACT 2901

<XX January 2014>

<Title> <Name> <Surname>
<Address 1>
<Address 2>
<SUBURB> <STATE> <Postcode>

Dear <Title> <Surname>

**Children in your family are eligible for dental benefits under the Child Dental Benefits Schedule**

Children in your family are eligible throughout 2014 for the Child Dental Benefits Schedule, a new dental program which replaces the Medicare Teen Dental Plan. The Child Dental Benefits Schedule provides up to $1,000 in benefits for basic dental services, capped over two consecutive calendar years.

A child is eligible for the Child Dental Benefits Schedule if he or she is aged between 2-17 years old for at least one day in the calendar year, is eligible for Medicare and is part of a family that receives a relevant Australian government payment such as Family Tax Benefit Part A. The child(ren) remain eligible all year, even if the payment that made them eligible stops this year or if they turn 18 this year.

**Eligible child(ren) and benefit cap amount(s)**
Listed below is/are the eligible child(ren) in your family and each child's benefit cap amount.

| Full name | Benefit cap amount* |
|---|---|
| <First name> <Surname> | $XXXX.XX |
| <First name> <Surname> | $XXXX.XX |
| <First name> <Surname> | $XXXX.XX |

* A child's benefit cap amount starts the year they first receive a dental service.

You can use the full benefit cap of $1,000 for each child in the first year. If the child does not use it all, you can use what is left in the second year if the child is still eligible. Any balance remaining at the end of the two year period cannot be used to fund services that are provided outside that two year period. A child's benefit cap can only be used for eligible services provided to that child.

**Eligible services**
The Child Dental Benefits Schedule provides individual benefits for a range of services including examinations, x-rays, cleaning, fissure sealing, fillings, root canals and extractions. Benefits are not available for orthodontic or cosmetic dental work and cannot be paid for any services provided in a hospital.

**What you need to do**
A benefit can only be paid for a dental service if the child has a balance remaining in his or her benefit cap. Before making an appointment, you can easily check your child's eligibility and remaining benefit cap amount, or view other family Medicare information, by accessing Medicare services through your myGov account at **my.gov.au** If you do not have a myGov account, you will need to create one first and then link it to Medicare.

Alternatively, you may phone 132 011 (call charges may apply – calls from mobile phones may be charged at a higher rate). You will need to have your child's Medicare card details with you to access this service. Your dentist can also check your child's eligibility and remaining benefit cap amount by contacting the Australian Government Department of Human Services.

When you make the appointment with either a private dentist or a state or territory public dental clinic let them know that you will be using the Child Dental Benefits Schedule.

At the appointment, the dentist is required to discuss your child(ren)'s treatment and its costs with the parent/guardian, or your child depending on his or her age, and obtain consent before treatment is provided. This consent will need to be confirmed by signing a form provided by the dentist.

Public dental clinics must bulk bill under the Child Dental Benefits Schedule, which means the benefit available under the Child Dental Benefits Schedule covers the cost of the service.

Private dentists may charge a fee that exceeds the benefit available for a service. If they do, you will have to pay the difference in cost. You cannot claim a benefit from both a private health insurer and the Child Dental Benefits Schedule for the same dental service. More information is at: **humanservices.gov.au/childdental**

**Shared Care arrangements**
If your child(ren) is/are in equal shared care arrangements, each parent or carer/guardian will receive a letter. Whilst either parent or carer can organise dental services for each child, that child's total benefit cap of $1000 cannot be exceeded.

**Receiving your Medicare letters online**
You can now access some of your Medicare letters online through your myGov Inbox. In future, you will also be able to receive letters about the Child Dental Benefits Schedule from your Inbox.

**Updating your family details**
If your circumstances have changed and you need to update your family details, you can do this by accessing your Centrelink services through your myGov account at **my.gov.au** You will need to link your myGov account to Centrelink first.

**More information**
For more information on the Child Dental Benefits Schedule, go to **humanservices.gov.au/childdental**

This notification relates to all of the services listed in the Dental Benefits Schedule.

Scan for more information:

Notes: Source: DoH (2016).

Appendix Figure A3: Example of self-print poster


Notes: Source: DoH (2019b).

Appendix Table B1: Determinants of uptake among eligible children – Remaining results

| Variables | MTDP | | CDBS | | Both | |
|---|---|---|---|---|---|---|
| | OLS | Probit | OLS | Probit | OLS | Probit |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Child age (months) | 21.81*** | 14.71*** | 3.09*** | 0.73** | 3.67*** | 1.08*** |
| | [3.37] | [2.20] | [1.11] | [0.33] | [1.07] | [0.31] |
| Child age (months) squared | -0.07*** | -0.05*** | -0.01*** | -0.00** | -0.01*** | -0.00*** |
| | [0.01] | [0.01] | [0.00] | [0.00] | [0.00] | [0.00] |
| Male | -2.08 | -1.21 | -3.34 | -0.63 | -2.71 | -0.80 |
| | [2.82] | [1.67] | [4.36] | [1.45] | [3.00] | [1.19] |
| Australian-born | 3.95 | 2.13 | 2.91 | -2.40 | 1.40 | -0.58 |
| | [9.07] | [5.44] | [20.27] | [7.18] | [10.53] | [4.96] |
| Aboriginal | -4.29 | -2.69 | -20.75** | -3.39 | -14.30** | -3.24 |
| | [6.64] | [4.89] | [9.72] | [3.96] | [6.79] | [3.29] |
| Low birthweight | -0.46 | -0.84 | 4.21 | -1.27 | 2.02 | -1.05 |
| | [5.55] | [3.36] | [8.63] | [2.83] | [5.73] | [2.28] |
| Breastfed at early childhood | 2.73 | 1.51 | 0.40 | 2.10 | 1.42 | 1.81 |
| | [3.11] | [1.90] | [4.90] | [1.59] | [3.35] | [1.32] |
| Mother's age (years) | 2.28 | 1.80 | -6.79* | -2.58** | -3.01 | -0.79 |
| | [2.29] | [1.59] | [4.06] | [1.26] | [2.67] | [0.98] |
| Mother's age squared | -0.02 | -0.02 | 0.08* | 0.03** | 0.04 | 0.01 |
| | [0.03] | [0.02] | [0.05] | [0.01] | [0.03] | [0.01] |
| Mother NESB migrant [(a)] | 3.21 | 1.79 | 5.68 | 2.78 | 4.42 | 2.24 |
| | [4.00] | [2.37] | [6.29] | [2.03] | [4.22] | [1.67] |
| Mother ESB migrant [(a)] | 4.62 | 2.83 | -11.77** | -2.59 | -5.77 | -0.31 |
| | [4.54] | [2.61] | [5.94] | [2.21] | [4.34] | [1.81] |
| Mother with certificate [(b)] | 2.33 | 1.43 | -7.19 | -2.10 | -2.53 | -0.35 |
| | [3.21] | [1.95] | [5.74] | [1.88] | [3.64] | [1.48] |
| Mother with higher degree [(b)] | 3.22 | 1.46 | -3.86 | -2.69 | -0.45 | -0.63 |
| | [4.22] | [2.42] | [6.94] | [2.31] | [4.55] | [1.82] |
| Number of siblings | -0.44 | -0.27 | 1.07 | 0.69 | 0.38 | 0.23 |
| | [1.25] | [0.75] | [1.93] | [0.64] | [1.34] | [0.54] |
| Lived with both parents | 0.90 | 0.80 | -6.59 | -0.84 | -3.32 | -0.11 |
| | [3.24] | [1.91] | [5.04] | [1.62] | [3.49] | [1.33] |
| Home - % completed year 12 for linked area | 0.14 | 0.11 | 0.06 | 0.08 | 0.13 | 0.10 |
| | [0.22] | [0.13] | [0.31] | [0.10] | [0.22] | [0.08] |
| Home - % family <$1K/week in linked area | 0.00 | 0.03 | 0.29 | -0.00 | 0.19 | 0.02 |
| | [0.18] | [0.11] | [0.26] | [0.08] | [0.19] | [0.07] |
| Metropolitan region | 0.74 | 0.29 | 9.18 | -1.22 | 6.81 | -0.31 |
| | [3.89] | [2.30] | [6.30] | [2.08] | [4.16] | [1.64] |
| Home - % speak English in linked area | 0.04 | 0.02 | -0.06 | -0.02 | -0.05 | -0.03 |
| | [0.21] | [0.13] | [0.29] | [0.09] | [0.21] | [0.08] |
| Home - % Australian born in linked area | 0.13 | 0.12 | -0.04 | 0.09 | 0.10 | 0.15 |
| | [0.30] | [0.18] | [0.46] | [0.15] | [0.31] | [0.12] |
| Home - % ATSI in linked area | -0.11 | -0.18 | -1.34** | -0.63*** | -0.76** | -0.49*** |

| Variables | MTDP | | CDBS | | Both | |
|---|---|---|---|---|---|---|
| | OLS | Probit | OLS | Probit | OLS | Probit |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | [0.25] | [0.24] | [0.59] | [0.22] | [0.34] | [0.19] |
| Second quarter [(c)] | 6.29 | 3.50 | 28.73*** | 7.05 | 20.95*** | 6.04 |
| | [9.62] | [5.96] | [10.93] | [4.78] | [8.06] | [3.77] |
| Third quarter [(c)] | 1.90 | 1.16 | 28.93*** | 6.70 | 18.70** | 4.81 |
| | [9.55] | [5.94] | [10.60] | [4.72] | [7.90] | [3.73] |
| Fourth quarter [(c)] | -8.79 | -5.00 | 22.01* | 6.28 | 11.34 | 2.47 |
| | [9.73] | [6.07] | [11.25] | [4.87] | [8.22] | [3.82] |
| VIC [(d)] | 18.27* | 11.18* | 26.69* | 6.01 | 22.39** | 7.62* |
| | [9.95] | [6.27] | [15.84] | [5.76] | [10.54] | [4.45] |
| QLD [(d)] | 14.22 | 10.19 | -2.16 | 0.70 | 3.95 | 3.79 |
| | [10.01] | [6.33] | [15.87] | [5.80] | [10.56] | [4.50] |
| SA [(d)] | 8.73 | 5.63 | 24.29 | 4.44 | 18.70* | 4.94 |
| | [9.91] | [6.31] | [16.00] | [5.77] | [10.64] | [4.48] |
| WA [(d)] | 20.97* | 12.34* | 5.89 | 2.41 | 12.26 | 6.32 |
| | [11.00] | [6.77] | [17.48] | [6.24] | [11.64] | [4.81] |
| TAS [(d)] | 6.92 | 4.72 | -37.38** | -19.44*** | -18.37 | -8.47* |
| | [10.83] | [6.91] | [17.13] | [6.61] | [11.29] | [5.02] |
| NT [(d)] | 20.02* | 11.88* | -1.12 | 5.57 | 8.49 | 7.86 |
| | [11.49] | [7.03] | [18.16] | [6.54] | [12.08] | [5.02] |
| ACT [(d)] | -17.17 | -9.83 | -40.77** | -19.32 | -29.61** | -14.89 |
| | [12.11] | [13.62] | [18.64] | [13.23] | [13.21] | [10.28] |
| Dental benefit year = 2012 [(e)] | -26.39*** | -17.12*** | | | 4.75 | 8.05*** |
| | [10.20] | [5.92] | | | [5.54] | [2.07] |
| Dental benefit year = 2013 [(e)] | -37.24*** | -22.61*** | | | -4.69 | 1.49 |
| | [10.26] | [5.64] | | | [5.58] | [2.05] |
| Dental benefit year = 2014 [(e)] | | | | | 44.30*** | 10.20*** |
| | | | | | [5.54] | [1.93] |
| Dental benefit year = 2015 [(e)] | | | -3.46 | 0.58 | 40.57*** | 10.80*** |
| | | | [4.36] | [1.17] | [5.50] | [1.95] |
| Dental benefit year = 2016 [(e)] | | | 8.33 | 5.58*** | 51.53*** | 15.48*** |
| | | | [6.11] | [1.83] | [6.99] | [2.36] |

Notes: Results from OLS regressions for continuous outcomes and probit regressions for binary outcomes. Marginal effects (coefficient estimates and standard errors are multiplied by 100 for aesthetic purposes) are reported for probit regressions. [(a), (b), (c)] and [(d)] indicates Australian-born mother, mother with no qualification, first quarter, and NSW as the base group, respectively. [(e)] indicates 2011 as the base group for MTDP and both regressions and 2014 for CDBS regressions. Robust standard errors clustered at the individual level in parentheses. The symbol *denotes significance at the 10% level, **at the 5% level, and ***at the 1% level.

Appendix Table B2: Determinants of uptake among eligible children – Regressions with different list of controls

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Child age (months) | 1.03*** | 1.03*** | 1.04*** | 1.02*** | 1.03*** | 1.04*** | 1.04*** | 1.07*** | 1.02*** | 0.56** |
| | [0.32] | [0.32] | [0.32] | [0.31] | [0.31] | [0.32] | [0.32] | [0.31] | [0.31] | [0.27] |
| Child age (months) squared | -0.00*** | -0.00*** | -0.00*** | -0.00*** | -0.00*** | -0.00*** | -0.00*** | -0.00*** | -0.00*** | -0.00** |
| | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] |
| Male | -1.31 | -1.25 | -0.92 | -1.30 | -1.28 | -1.28 | -1.27 | -1.31 | -1.28 | -0.81 |
| | [1.20] | [1.20] | [1.20] | [1.20] | [1.20] | [1.19] | [1.20] | [1.19] | [1.20] | [1.20] |
| Australian-born | -0.76 | -0.72 | -0.78 | -0.80 | -0.71 | -1.39 | -0.47 | -0.33 | -0.75 | 1.52 |
| | [4.88] | [4.89] | [4.89] | [4.87] | [4.89] | [4.96] | [4.88] | [4.89] | [4.87] | [4.98] |
| Aboriginal | -5.79* | -5.79* | -5.28 | -6.03* | -5.89* | -4.57 | -5.43 | -4.16 | -5.90* | -3.52 |
| | [3.32] | [3.31] | [3.32] | [3.31] | [3.34] | [3.29] | [3.33] | [3.32] | [3.33] | [3.34] |
| Low birthweight | -1.72 | -1.70 | -1.58 | -1.75 | -1.69 | -1.66 | -1.66 | -1.30 | -1.70 | -1.52 |
| | [2.29] | [2.28] | [2.28] | [2.28] | [2.29] | [2.29] | [2.28] | [2.28] | [2.28] | [2.29] |
| Breastfed at early childhood | 2.91** | 2.90** | 2.69** | 2.92** | 2.94** | 2.56* | 2.83** | 2.18* | 2.92** | 1.68 |
| | [1.33] | [1.33] | [1.33] | [1.33] | [1.33] | [1.33] | [1.33] | [1.32] | [1.33] | [1.33] |
| Mother's age (years) | -0.55 | -0.53 | -0.61 | -0.43 | -0.47 | -0.91 | -0.54 | -0.87 | -0.49 | -0.82 |
| | [0.99] | [0.99] | [0.98] | [0.99] | [0.99] | [0.99] | [0.98] | [0.98] | [0.99] | [0.99] |
| Mother's age squared | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] |
| Mother NESB migrant (a) | 3.01* | 3.05* | 2.93* | 2.79* | 2.86* | 3.00* | 3.16* | 2.80* | 2.91* | 1.45 |
| | [1.67] | [1.67] | [1.67] | [1.67] | [1.68] | [1.66] | [1.68] | [1.67] | [1.67] | [1.68] |
| Mother ESB migrant (a) | -0.85 | -0.84 | -0.88 | -0.78 | -0.97 | -0.60 | -0.79 | -0.42 | -0.82 | -0.21 |
| | [1.81] | [1.81] | [1.81] | [1.81] | [1.82] | [1.81] | [1.81] | [1.81] | [1.81] | [1.82] |
| Mother with certificate (b) | -0.04 | -0.05 | -0.08 | -0.02 | 0.00 | -0.17 | 0.03 | -0.42 | -0.04 | 0.37 |
| | [1.50] | [1.50] | [1.49] | [1.50] | [1.50] | [1.49] | [1.49] | [1.49] | [1.50] | [1.48] |
| Mother with higher degree (b) | 0.32 | 0.29 | 0.17 | 0.61 | 0.46 | -0.16 | 0.24 | -0.71 | 0.24 | 0.20 |
| | [1.82] | [1.82] | [1.82] | [1.83] | [1.83] | [1.82] | [1.82] | [1.82] | [1.82] | [1.82] |
| Number of siblings | 0.13 | 0.13 | 0.18 | 0.22 | 0.12 | 0.20 | 0.11 | 0.04 | 0.13 | 0.26 |
| | [0.55] | [0.55] | [0.55] | [0.55] | [0.55] | [0.54] | [0.55] | [0.55] | [0.55] | [0.54] |
| Lived with both parents | 1.78 | 1.79 | 1.59 | 2.63** | 1.85 | 0.09 | 1.34 | 0.47 | 1.85 | -0.01 |
| | [1.23] | [1.23] | [1.23] | [1.29] | [1.23] | [1.28] | [1.24] | [1.24] | [1.23] | [1.33] |
| Child had cavities | | -1.18 | | | | | | | | -0.52 |

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | [2.69] | | | | | | | | [2.67] |
| Child had teeth filled due to decay | | 2.15 | | | | | | | | 1.92 |
| | | [2.74] | | | | | | | | [2.73] |
| Child had teeth pulled due to decay | | -0.35 | | | | | | | | 1.38 |
| | | [2.91] | | | | | | | | [2.90] |
| Child had accidental tooth damage | | -0.83 | | | | | | | | -0.92 |
| | | [2.86] | | | | | | | | [2.90] |
| Child brushed teeth twice or more | | | 3.92*** | | | | | | | 2.92*** |
| | | | [1.10] | | | | | | | [1.10] |
| Household income (log) | | | | -1.80** | | | | | | -2.44*** |
| | | | | [0.76] | | | | | | [0.78] |
| Had private health insurance | | | | | -1.01 | | | | | -2.13 |
| | | | | | [1.36] | | | | | [1.36] |
| Lived in an owned home | | | | | | 5.82*** | | | | 5.31*** |
| | | | | | | [1.28] | | | | [1.29] |
| Mother had depression | | | | | | | -3.15*** | | | -2.60** |
| | | | | | | | [1.13] | | | [1.13] |
| Mother smoked | | | | | | | | -8.50*** | | -7.71*** |
| | | | | | | | | [1.45] | | [1.47] |
| Dental practitioner density | | | | | | | | | 0.84 | 0.97 |
| | | | | | | | | | [0.63] | [0.66] |
| Observations | 9,958 | 9,958 | 9,958 | 9,958 | 9,958 | 9,958 | 9,958 | 9,958 | 9,958 | 9,958 |
| Pseudo R2 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.02 | 0.03 | 0.02 | 0.02 |

Notes: Results are from probit regressions for a pooled sample of both programs. Marginal effects (coefficient estimates and standard errors are multiplied by 100 for aesthetic purposes) are reported. [(a)] and [(b)] indicates Australian-born mother and mother with no qualification as the base group, respectively. Other explanatory variables include local socio-economic background variables, state/territory dummies, year dummies, and survey quarters. Robust standard errors clustered at the individual level in parentheses. The symbol *denotes significance at the 10% level, **at the 5% level, and ***at the 1% level.

Appendix Table B3: Determinants of uptake among eligible children – Regressions by year

| | MTDP | | | CDBS | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2014-15 | 2015-16 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Child age (months) | 123.0*** | 10.8 | -71.2* | -0.2 | 2.3 | 6.0 | 3.0 | 6.6 |
| | [27.3] | [38.0] | [38.2] | [5.2] | [5.0] | [7.3] | [7.7] | [8.2] |
| Child age (months) squared | -0.5*** | -0.0 | 0.2* | 0.0 | -0.0 | -0.0 | -0.0 | -0.0 |
| | [0.1] | [0.1] | [0.1] | [0.0] | [0.0] | [0.0] | [0.0] | [0.0] |
| Child had cavities | 1.8 | 10.8 | 9.0 | 39.1 | -0.2 | -9.7 | 44.9 | -23.2 |
| | [10.1] | [12.4] | [12.6] | [24.1] | [18.9] | [22.3] | [28.1] | [28.9] |
| Child had teeth filled due to decay | -2.2 | -10.9 | -13.4 | -6.0 | 24.7 | 21.3 | -3.4 | 69.8** |
| | [10.4] | [12.9] | [13.1] | [24.0] | [18.9] | [22.5] | [28.4] | [29.6] |
| Child had teeth pulled due to decay | -22.7* | -11.1 | -5.6 | -9.2 | -22.3 | 16.0 | -16.5 | -17.8 |
| | [12.2] | [20.8] | [13.7] | [21.7] | [18.1] | [24.8] | [27.8] | [30.5] |
| Child had accidental tooth damage | -8.2 | 2.0 | 8.1 | 0.4 | 1.5 | 4.5 | 15.9 | 7.9 |
| | [7.4] | [9.8] | [11.1] | [19.6] | [17.5] | [25.2] | [30.1] | [31.2] |
| Child brushed teeth twice | 3.1 | 7.4* | 7.0 | -0.9 | 9.3 | 10.7 | 9.0 | 24.2** |
| | [3.7] | [4.5] | [4.3] | [7.4] | [6.4] | [8.2] | [10.4] | [11.1] |
| Household income (log) | 1.3 | -0.0 | -6.3 | -4.3 | -9.7* | -5.5 | -8.6 | -25.8** |
| | [3.5] | [2.8] | [4.2] | [4.8] | [5.5] | [5.5] | [6.7] | [10.4] |
| Had private health insurance | -1.3 | -1.9 | -7.6 | -7.8 | -18.6*** | -3.7 | -30.0*** | -27.5** |
| | [4.4] | [5.3] | [5.2] | [8.1] | [7.0] | [9.3] | [11.3] | [12.1] |
| Lived in an owned home | 6.5 | 4.5 | 18.6*** | 15.1* | 16.4** | 7.2 | 25.4** | 20.8* |
| | [4.1] | [5.0] | [4.8] | [8.3] | [7.2] | [9.0] | [11.6] | [12.5] |
| Mother had depression | -2.1 | -6.2 | -11.7*** | -11.1 | -9.6 | 8.1 | -15.5 | -6.4 |
| | [3.7] | [4.6] | [4.2] | [7.1] | [6.5] | [8.4] | [10.5] | [11.4] |
| Mother smoked | -11.3*** | -16.7*** | -14.9*** | -12.0 | -11.8 | -3.6 | -22.0* | -16.5 |
| | [4.3] | [5.4] | [4.9] | [9.4] | [8.3] | [10.1] | [13.3] | [14.7] |
| Dental practitioner density | 7.8** | -4.3 | -0.2 | 1.6 | 0.3 | -1.5 | 1.3 | 0.5 |
| | [3.8] | [4.6] | [3.0] | [4.0] | [2.5] | [2.5] | [6.4] | [4.2] |
| Observations | 1,548 | 1,264 | 1,240 | 2,178 | 2,223 | 1,506 | 2,178 | 1,907 |
| R-squared | 0.08 | 0.06 | 0.07 | 0.04 | 0.04 | 0.05 | 0.05 | 0.06 |

Notes: Results are from probit regressions. Marginal effects (coefficient estimates and standard errors are multiplied by 100 for aesthetic purposes) are reported. Other explanatory variables include characteristics of the child, the mother and the household, local socio-economic background variables, state/territory dummies, survey year and quarter dummies. Robust standard errors clustered at the individual level in parentheses. The symbol *denotes significance at the 10% level, **at the 5% level, and ***at the 1% level.

Appendix Table B4: Determinants of child dental benefit eligibility

| Variables | Marginal effects (x100) |
|---|---|
| Mother's age (years) | -1.30* |
| | [0.77] |
| Mother's age squared | 0.02* |
| | [0.01] |
| Mother NESB migrant [(a)] | -1.83* |
| | [1.01] |
| Mother ESB migrant [(a)] | -1.46 |
| | [1.06] |
| Mother with certificate [(b)] | -1.95** |
| | [0.95] |
| Mother with higher degree [(b)] | -7.72*** |
| | [1.06] |
| Number of children aged 0-17 years old | 6.83*** |
| | [0.49] |
| Number of children aged 18-21 years old | 3.51*** |
| | [0.52] |
| Number of children aged 22 or over | 6.03*** |
| | [0.78] |
| Lived with both parents | -13.70*** |
| | [0.87] |
| Child had cavities | 4.62*** |
| | [1.63] |
| Child had teeth filled due to decay | -4.30*** |
| | [1.66] |
| Child had teeth pulled due to decay | -2.36 |
| | [1.71] |
| Child had accidental tooth damage | 1.66 |
| | [1.50] |
| Child brushed teeth twice or more | -3.07*** |
| | [0.66] |
| Household income (log) | -2.59*** |
| | [0.48] |
| Had private health insurance | -7.01*** |
| | [0.78] |
| Lived in an owned home | -9.94*** |
| | [0.84] |
| Mother had depression | 4.13*** |
| | [0.65] |
| Mother smoked | -0.31 |
| | [0.98] |
| Dental practitioner density | 0.98*** |
| | [0.35] |
| Household income under cut-offs | 25.50*** |
| | [0.74] |
| Observations | 26,752 |
| Pseudo R2 | 0.31 |

Notes: Results (marginal effects, coefficient estimates and standard errors are multiplied by 100 for aesthetic purposes) are from a probit model in the sample selection correction framework for a pooled sample of both programs. [(a)] and [(b)] indicates Australian-born mother and mother with no qualification as the base group, respectively. Other explanatory variables include child characteristics (age, gender, nativity, Aboriginal, birthweight, breastfed at early childhood), local socio-economic background variables, state/territory dummies, year dummies, and survey quarter dummies. Robust standard errors clustered at the individual level in parentheses. The symbol *denotes significance at the 10% level, **at the 5% level, and ***at the 1% level.

Appendix Table B5: Eligibility and uptake of child dental benefits for LSAC K cohort children – Using administrative data to calculate eligibility

| | 2011 | 2012 | 2013 | 2014 | 2015 | 2011-15 |
|---|---|---|---|---|---|---|
| | MTDP | | | CDBS | | |
| Eligible (%) | 68.5 | 64.3 | 60.9 | 59.8 | 55.1 | 61.4 |
| Uptake rate (% among eligible) | 25.0 | 33.2 | 30.2 | 32.4 | 32.8 | 30.7 |
| Mean of benefit claimed per visit (A$, conditional on uptake) | 154.2 | 158.1 | 161.9 | 281.0 | 281.0 | 210.9 |
| Standard deviation of benefit per visit (A$, conditional on uptake) | 20.5 | 19.3 | 18.1 | 175.2 | 164.1 | 127.6 |
| Had to pay out of pocket (%, conditional on uptake) | 0.0 | 0.0 | 2.3 | 8.6 | 4.3 | 3.2 |
| Number of dental visits per year (conditional on uptake) | 1.0 | 1.0 | 1.0 | 1.8 | 1.7 | 1.3 |

Notes: Figures are adjusted for sampling weights. Sample: 2,807 K-cohort children who gave consent to have their administrative ISH records to be linked to LSAC data. Eligibility is identified using Centrelink's ISH measured in the financial year prior to the year of uptake.

Appendix Table B6: Eligibility and uptake of child dental benefits for LSAC K cohort children – Using self-reported ISH to calculate eligibility

| | 2011 | 2012 | 2013 | 2014 | 2015 | 2011-15 |
|---|---|---|---|---|---|---|
| | MTDP | | | CDBS | | |
| Eligible (%) | 51.5 | 44.4 | 44.4 | 41.8 | 41.8 | 44.6 |
| Uptake rate (% among eligible) | 23.8 | 30.9 | 28.5 | 34.0 | 31.8 | 29.8 |
| Mean of benefit claimed per visit (A$, conditional on uptake) | 154.7 | 157.1 | 160.6 | 283.4 | 275.0 | 212.2 |
| Standard deviation of benefit per visit (A$, conditional on uptake) | 18.5 | 21.4 | 21.8 | 179.5 | 158.2 | 129.6 |
| Had to pay out of pocket (%, conditional on uptake) | 0.0 | 0.0 | 2.2 | 7.4 | 3.9 | 3.0 |
| Number of dental visits per year (conditional on uptake) | 1.0 | 1.0 | 1.0 | 1.8 | 1.7 | 1.3 |

Notes: Figures are adjusted for sampling weights. Sample: 2,807 K-cohort children who gave consent to have their administrative ISH records to be linked to LSAC data. Eligibility is identified using self-reported ISH and Eligibility Rule 1 (see Appendix Table A2 for details).

Appendix Table B7: Determinants of uptake - different control variables

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mother K6 (reversed) | -0.45*** | | | | | | | | | | | |
| | [0.13] | | | | | | | | | | | |
| Mother was frequent binge drinker | | -0.07 | | | | | | | | | | |
| | | [1.59] | | | | | | | | | | |
| Father had depression | | | 0.27 | | | | | | | | | |
| | | | [1.66] | | | | | | | | | |
| Father smoked cigarette | | | | -2.88 | | | | | | | | |
| | | | | [1.97] | | | | | | | | |
| Father was frequent binge drinker | | | | | 1.50 | | | | | | | |
| | | | | | [2.02] | | | | | | | |
| Child had any problem with teeth | | | | | | 0.71 | | | | | | |
| | | | | | | [1.11] | | | | | | |
| Child had no treatment as a result of cavity | | | | | | | -2.16 | | | | | |
| | | | | | | | [3.34] | | | | | |
| Child had tooth pain | | | | | | | | 2.88** | | | | |
| | | | | | | | | [1.25] | | | | |
| Child had tooth pain when eating/drinking something hot/cold/sweet | | | | | | | | | 2.66** | | | |
| | | | | | | | | | [1.10] | | | |
| Child had teeth that are dark in colour | | | | | | | | | | 1.32 | | |
| | | | | | | | | | | [1.73] | | |
| Child had gum pain | | | | | | | | | | | 2.36 | |
| | | | | | | | | | | | [1.64] | |
| Child had blood on toothbrush after brushing teeth | | | | | | | | | | | | 0.09 |
| | | | | | | | | | | | | [1.11] |
| Observations | 11,077 | 10,545 | 5,568 | 5,669 | 5,396 | 11,325 | 8,194 | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 |

Notes: Results (marginal effects, coefficient estimates and standard errors are multiplied by 100 for aesthetic purposes) are from a probit model for a pooled sample of both programs. Marginal effects are calculated at the means of continuous variables. Other explanatory variables include characteristics of the child, the mother and the household, local socio-economic background variables, state/territory dummies, survey year and quarter dummies. Robust standard errors clustered at the individual level in parentheses. The symbol *denotes significance at the 10% level, **at the 5% level, and ***at the 1% level.