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Who's declining the "free lunch"? New evidence from the uptake of public child dental benefits

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. 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%). We also find some indicative evidence that a lack of information is a barrier to uptake.

Keywords: Government Programs; Impact Evaluation, Dental Health, Provision and Effects of Welfare Programs, Australia, Uptake, Take-up
JEL classifications: D91, H51, I12, I18, I38

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 theoretical 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), and further research is required to explore other factors that may drive non-uptake.

This paper makes four potentially important contributions to this literature. It does so by exploring (for the first time) the determinants of non-uptake of two recent public dental benefit programs for Australian children and adolescents from disadvantaged families (DoH 2019c). The unique features of these two programs enable us to contribute to the literature in four important ways. First, 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 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.

Second, 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). Third, 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). Fourth, 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 as the former are probably more likely to receive mail describing this public program. 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

In Australia, dental services are predominantly provided on the private market and, historically, the Australian Medicare scheme did not include Medicare Benefits Schedule Items for dentistry services. The states and territories did, and do, provide public dental services to eligible adults (mostly concession card holders and children) and children's dental services were, and are, available through a number of state-based schemes for children such as school dental visits and public oral health clinics. These services and the eligibility requirements differed considerably by state. For instance, the states of Western Australia, Queensland and South Australia have historically had dedicated school dental programs; while the Northern Territory used a hybrid model consisting of community□based services and school dental programs. In other States, such as New South Wales, Victoria, Tasmania and in the Australian Capital Territory, community□based clinics were the primary mode for the delivery of public dental health services for children (National Advisory Council on Dental Health - NACODH 2012). In principle, children are also given priority hospital treatment, with low waiting times, although the waiting list for tooth extractions under general anaesthetic was sometimes as long as two years (NACODH 2012). Private fee-for-service (FFS) dentistry items were not, however, historically included on the Medicare Benefits Schedule (MBS). This changed in 2004 for adults with chronic diseases whose extended treatment plans (ETPs) included an eligibility for dental services. As a result of this and other Commonwealth initiatives (which, for children, are discussed below), total public expenditure on dental health (including expenditures on initiatives such as water fluoridation and the provision of hospital dental services) had increased to approximately 24% of total direct Australian dental expenditures (8% by the states/territories and 16% by the Commonwealth) by 2009-10 (NACODH 2012).[1] Around that time, approximately 84.3% of Australia's dentists worked in private practice, 1.2% were employed on school dental programs, 5.1% were employed in dental hospitals, 4.8% in general public dental programs, and 4.6% in "public health-other" roles (Balasubramanian & Teusner 2011, Figure 6 p. 12).

In 2008 the Australian Government introduced the Medicare Teen Dental Plan (MTDP) to improve dental health of teenagers in disadvantaged families under the Dental Benefits Act 2008 and its subordinate Rules (DoH 2012). The MTDP was introduced in the light of evidence

[1] Prior to earlier Commonwealth initiatives in the mid-1990s the states and territories accounted for 80% of public dental services direct expenditure: by 2009-10 their share had declined to 39% and the Commonwealth's had increased to 61% (NACODH 2012).

of poor dental health outcomes and usage patterns for low income households in the 2003-04 Child Dental Health Survey (Armfield *et al.* 2009). Under the MTDP, the Government provided dental benefits of up to Australian dollar (A$) 150 per calendar year 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 to receive a preventive dental check.

Several years after the introduction of the MTDP scheme, though, survey evidence showed that approximately one-in-five Australian children were not having annual dental visits and were seeing the dentist to attend to a problem, rather than as a preventive measure (NACODH 2012). In the meantime, survey evidence had shown unfavourable dental attendance patterns for approximately 30% of Australians (where an unfavourable pattern is characterised by irregular visits, often for dental problems) with a pronounced income gradient: 16.1% of the highest-income households and 43.7% of the lowest-income households had unfavourable attendance patterns (Ellershaw & Spencer 2011). The National Children's Oral Health Survey (2012-2014) produced additional results on the relationship between children's use of dental services and indicators of their dental health (e.g., untreated dental problems). The resulting statistics confirmed wide income-related disparities: children from the poorest households had almost twice the rate (35.9%) of untreated caries in the primary dentition as children from the wealthiest households (18.3%) (Ha *et al.* 2016). Other correlates of the prevalence of untreated caries in children were parental education, Indigenous identity, country of birth, residential location and the reason for their last dental visit.

The relatively modest provisions of the MTDP were thus eventually 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).

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. 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 **Error! Reference source not found.**) while it is a notification letter in the second program (**Error! Reference source not found.**).[2] 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). Furthermore, the transactions costs associated with taking up benefits are not large: parents must sign a consent form, which can be done at the dental practice at the time of the appointment, following verbal consent over the phone. The consent form includes an informed financial consent component too, which requires the parent or guardian to sign an acknowledgement of their responsibility for any out-of-pocket fees that will be charged. The child's eligibility may be shown to the dental practice using the letter that is mailed, or emailed, to eligible households. These data are also stored in the MyGov website system and mobile app that have been used for many Australian Government services since July 2014. If none of these methods is available to the parent at the time of the appointment, either the parent or practice may phone an eligibility hotline provided by the Department of Health (DoH 2019c). Thus, the expected costs of using the CDBS program, which provides considerable in-kind benefits to households, are generally quite low.

[Insert Figure 1 here]

The temporal development of these two 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.[3] Furthermore, despite the Government's attempts to

[2] Information about the programs is also made available at some dental practitioners' practices via posters or pamphlets (see **Error! Reference source not found.** for an example).

[3] 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 uptake rates for all years.

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, 2019c), 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-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 **Error! Reference source not found.**) 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 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. 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 **Error! Reference source not found.**.

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. 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. This calculated 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. The differences in uptake rates between MTDP and CDBS are probably linked to the differences in their designs, including the amount of benefits and the way the programs were communicated. 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:

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

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 α, β and γ 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.[4] Parental characteristics are included in our empirical model because parents are typically the decision-makers regarding the health 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 more deprived 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

[4] Variable definitions and summary statistics are provided in **Error! Reference source not found.**.

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), maternal employment status and private health insurance status in $Y_{i,t-1}$ as they may provide families with substitutable financial resources to pay for children's dental care (Gnanamanickam *et al.* 2018). As compared to unemployed mothers, employed mothers have less time available to perform other non-work related activities, including taking their children to the dentist, the inclusion of maternal employment status may also capture the potential role of time constraints in determining the take-up of the public benefits..

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. For instance, the mother's education can influence the uptake via the informational barrier channel (as mentioned above) as well as the cognitive barrier channel because, other things being equal, mothers with higher education may face a lower cognitive barrier in taking up the benefits.[5] 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.[6] 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.[7]

[5] Our data also show that mothers with higher qualification as measured by having a bachelor degree are less likely to have depression.

[6] Nevertheless, we experimented with estimating equation (1) by calendar year. Estimates (reported in **Error! Reference source not found.**) while lacking statistical power due to the small sample size are usually in line with the pooled results (reported in Table 3).

[7] 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 **Error! Reference source not found.**, 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

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), employed mothers (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.[8] The results show that the child's previous oral health conditions do not drive the decision to take 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

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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.

[8] **Error! Reference source not found.** 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 (re-reported in Column 10 of **Error! Reference source not found.**). The similarity in the results suggests that each variable in the extended control list has a separate impact on the uptake. **Error! Reference source not found.** 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.

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$5 more benefits or are 3 percentage points (or 12%) 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 6.83 cents, or 0.04 percentage points. Similarly, relative to children from families without private health insurance, those with private health insurance take up A$11 less from CDBS or are less likely to take up by 3 percentage points (or 10%). 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). 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 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$11 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.[9] 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. 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$6 less or are 2.4 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 7.4 percentage points (or 27%) less likely to take up the benefits. The estimate of the mother's employment status from Table 3 is positive and statistically significant at the 5% level in the probit regression on CDBS and the two programs, indicating a potentially insignificant role of time constraint induced by maternal employment in determining the uptake.

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 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).

[9] Families registered with MBS/PBS are obligated to keep their addresses up to date. Unfortunately, we have no further information about how this policy is implemented in practice (DoH 2019c).

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. Likewise, regression results for remaining variables (reported in **Error! Reference source not found.**) 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. 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.[10] Moreover, ESB mothers take up $11 from CDBS benefits less than Australian-born mothers, suggesting a potential role of "lack of information" (e.g., local knowledge on dental services) in driving uptake. Finally, estimates of some temporal and geographical variables are highly statistically significant, validating their inclusion as controls in the regressions.[11]

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 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. It is interesting to observe no significant effect of

[10] 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). Our finding of a lower uptake rate by children with an Aboriginal background coupled with evidence of a higher incidence of untreated caries among Aboriginal children (Ha *et al.* 2016) suggest that policies to improve take-up rates of dental benefits should be targeted at this more disadvantageous group.

[11] While we observe some differences in the uptake by state/territory, such differences are not consistent across statistical models (i.e., OLS or Probit) and programs (i.e., MTDP, CDBS or both). For instance, while children in Tasmania have the lowest probability of taking up CDBS (from the Probit regression) children in the ACT take up the least this kind of benefit (from the OLS regression). Furthermore, we do not observe any difference in the take-up (in the probability and amount) of MTDP by children in Tasmania and the ACT and those in other states/territories. This inconsistency in the results and the small number of observations by state/territory in our data prevent us from making a robust analysis into the sources of the differential utilization rates by state/territory. We leave the issue for future research, as recommended in the most recent governmental report on CDBS (DoH 2019c).

household income and private health insurance on the uptake of MTDP (inconsistent with "welfare stigma" interpretation) and no significant effect of maternal depression on CDBS uptake (inconsistent with "cognitive biases" interpretation). As discussed in Section 2, differences between the two programs, including the generosity of dental benefits and the way the programs were communicated, may give rise to these contrasts.

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. 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 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 **Error! Reference source not found.** 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.[12]

[Insert Table 4 here]

[12] 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 **Error! Reference source not found.**), 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 -0.47 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 statistically significant in the baseline regression (rereported in Column 1) to 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 9 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 benefits. Additional results from the eligibility determinant equation (reported in **Error! Reference source not found.**) show that these children are also more likely to be targeted by the two child dental benefit programs.[13] Specifically, the results indicate that children living in rented homes, having mothers with depression 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.

[13] Other results from the eligibility determinant regression in **Error! Reference source not found.** 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 959, 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 **Error! Reference source not found.** 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.[14] **Error! Reference source not found.** 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 **Error! Reference source not found.**). The difference in eligibility rates using

[14] 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 were ineligible for any type of government support as an outcome of means-testing during the whole period from 2003 to 2015 (AIFS 2018). They are therefore identified as ineligible for dental benefits in this study.

administrative and self-reported data sources documented in this study is consistent with the oft-observed pattern of individuals under-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. **Error! Reference source not found.** 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). **Error! Reference source not found.** indicates that using maternal K6[15] 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 **Error! Reference source not found.**).[16] 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.* 2020). We also explore the degree of intertemporal persistence in the take-up of the benefits by including a one-year lagged take-up indicator as an additional explanatory variable in the uptake equation. The results from this exercise (reported in column 6 of **Error! Reference source not found.**) suggest a high level of persistence in the uptake since eligible families who accessed the benefits in the previous year are about 29 percentage points more likely to take up the benefits in the following year. These results also suggest that information/experience with the programs matters.

[15] The K6 was constructed from responses to 6 items which asked the mother about symptoms of depression or anxiety experienced in the last 4 weeks. The 6 questions asked are: "In the past 4 weeks, how often did you feel…: 1. Nervous, 2. Hopeless, 3. Restless or fidgety, 4. Everything was an effort, 5. So sad couldn't cheer up, and 6. Worthless". Responses range from "all of the time" (1) to "none of the time" (5). Unfortunately, our data do not have information on diagnosed anxiety (Le & Nguyen 2017).

[16] Unreported results show the estimates of paternal education and migration status are not statistically significant either. Our finding of an insignificant association between parental education and uptake of child dental benefits when viewed with a finding of a significant correlation between parental education and children's untreated caries found in the study by Ha *et al*. (2016) suggest a different role of parental education in explaining these two dental health behaviours.

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. 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 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 2.4 percentage points (or 9%) less likely to claim the benefits for their children. Similarly, smoking mothers are 7.4 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). Our findings provide empirical support for a potential intervention recommended by a Review Committee of the Department of Health to make eligibility letters look more like vouchers (DoH 2019c) as this may help to convey the purpose of the scheme better and improve uptake. Furthermore, the finding that the patterns of the determinants are not universal across both programs suggests a potentially significant role for designs of future programs, including the benefit sizes and the communication methods, to reduce both welfare stigma and cognitive biases regarding program take-up. 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. Additionally, 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.

Another important consideration is the role of institutions across the different states and territories of Australia and the role that these may play in influencing uptake. While we were able to control for these differences with state/territory fixed-effects, our data do not enable us to undertake any fine-grained study of the influence of differences in the institutional arrangements by region that are likely to affect uptake. As has been noted by the Department of Health (2019c), the uptake of the program was considerably higher for the two states (South Australia and Tasmania) that used extensive public delivery to bill for services under the program, while its uptake was lowest in the state with the highest proportion of private delivery (New South Wales). At the same time, the Department notes that consent problems were greatest in those states due to the requirement for informed consent to be provided in advance due to the delivery of services in schools on fixed dates, for example. This is not only an important policy consideration, but an important consideration for economic studies of methods to increase the uptake of dental health services under the CDBS: differences in institutional structures may mean that promising results from an experiment in one jurisdiction (e.g., NSW) have less external validity for some others (e.g., SA, Tasmania). In this respect, while the CDBS is a national initiative, research at the state and territory level may be required to improve the prospective uptake of dental services that are subsidised under the Scheme.

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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
Number of observations	4,102	3,909	3,909	7,154	7,154	6,341	32,569

Notes: Figures are adjusted for sampling weights. Eligibility Rule 1 (see **Error! Reference source not found.** for details) is used. Number of observations indicate the number of LSAC children who were eligible for dental benefits due to their ages in the observed year and are linked to Medicare data.

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

	MTDP			CDBS		
	Uptake	No uptake	(1) - (2)	Uptake	No uptake	(4) - (5)
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Child age (months)	146.86	145.14	1.72***	157.93	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)	41.92	40.74	1.18***	42.20	42.20	0.00
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	0.19	0.16	0.03**	0.20	0.19	0.01
Number of siblings	1.84	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	0.27	0.00
Child had teeth filled due to decay	0.21	0.21	0.00	0.21	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	0.03**
Household yearly income (A$1,000)	78.30	76.54	1.76	75.10	81.80	-6.7***
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 employed	0.66	0.60	0.06***	0.65	0.62	0.03
Mother had depression	0.35	0.43	-0.08***	0.37	0.41	-0.04**
Mother smoked cigarette	0.17	0.30	-0.12***	0.20	0.26	-0.06***
Dental practitioner density	0.81	0.79	0.02	0.94	0.84	0.09*
Number of observations	1074	2971		1937	3956	

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		Both	
	OLS	Probit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Child had cavities	5.78	2.49	13.05	-1.81	8.42	-0.53
	[7.07]	[4.23]	[12.10]	[3.22]	[8.31]	[2.68]
Child had teeth filled due to decay	-6.56	-2.88	10.54	3.87	4.70	1.55
	[7.29]	[4.38]	[12.08]	[3.25]	[8.47]	[2.74]
Child had teeth pulled due to decay	-14.26	-7.60	-8.34	0.47	-6.06	-0.53
	[9.61]	[6.38]	[11.86]	[3.25]	[9.41]	[2.90]
Child had accidental tooth damage	-2.28	-0.85	3.75	0.59	0.54	-0.61
	[5.72]	[3.66]	[12.46]	[3.96]	[7.20]	[2.91]
Child cleaned teeth twice or more	5.49**	3.56**	5.29	2.85**	5.42*	3.17***
	[2.59]	[1.56]	[4.38]	[1.39]	[2.86]	[1.09]
Household income (log)	-2.11	-1.11	-6.83**	-3.59***	-5.07**	-2.60***
	[2.21]	[1.25]	[3.20]	[0.98]	[2.37]	[0.78]
Had private health insurance	-3.28	-1.04	-10.62**	-3.05*	-7.91**	-2.13
	[3.45]	[1.95]	[4.99]	[1.65]	[3.48]	[1.35]
Home owner	8.93***	5.45***	12.82***	4.76***	11.25***	5.08***
	[3.02]	[1.86]	[4.95]	[1.61]	[3.32]	[1.29]
Mother employed	3.72	1.94	6.44	3.77**	5.24	2.80**
	[3.06]	[1.86]	[4.78]	[1.59]	[3.21]	[1.29]
Mother had depression	-6.48**	-3.43**	-5.87	-1.54	-6.30**	-2.37**
	[2.72]	[1.64]	[4.37]	[1.41]	[2.91]	[1.13]
Mother smoked	-14.53***	-9.81***	-9.86*	-5.30***	-12.01***	-7.37***
	[3.16]	[2.13]	[5.51]	[1.82]	[3.61]	[1.46]
Dental practitioner density	1.16	0.73	0.26	0.88	0.64	0.91
	[2.77]	[1.39]	[2.55]	[0.69]	[2.18]	[0.63]
Observations	4,045	4,045	5,893	5,893	9,938	9,938
R2 (Pseudo R2 for Probit)	0.05	0.05	0.03	0.03	0.05	0.03

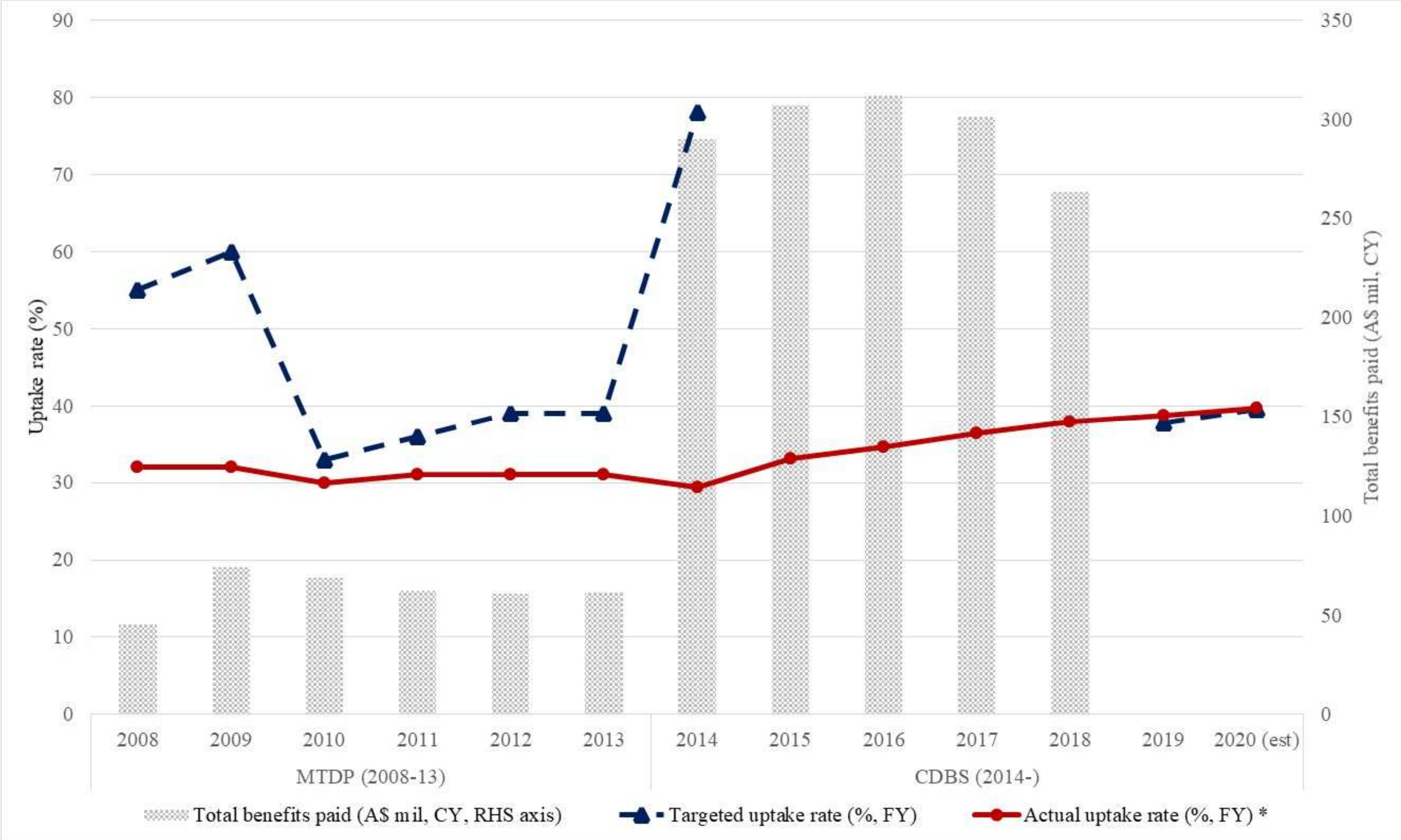
Notes: Results from OLS regressions for continuous outcomes and probit regressions for binary outcomes. Marginal effects (coefficient estimates and standard errors are multiplied by 100 for aesthetic purposes) are reported for probit regressions. Other explanatory variables include characteristics of the child, the mother and the household, local socio-economic background variables, state/territory dummies, survey year and quarter dummies (reported in **Error! Reference source not found.**). 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	-0.53	-2.41	-0.75	-1.24	-3.14	4.47
	[2.68]	[2.89]	[2.92]	[2.63]	[2.78]	[4.74]
Child had teeth filled due to decay	1.55	3.63	2.01	2.20	4.81*	-3.43
	[2.74]	[2.96]	[3.01]	[2.69]	[2.84]	[4.90]
Child had teeth pulled due to decay	-0.53	-0.45	-0.67	0.26	0.64	-1.33
	[2.90]	[3.19]	[3.26]	[2.87]	[3.01]	[6.26]
Child had accidental tooth damage	-0.61	-0.53	0.17	-0.19	-1.13	-2.79
	[2.91]	[3.11]	[3.21]	[2.80]	[2.85]	[3.94]
Child brushed teeth twice or more	3.17***	4.01***	3.64***	3.13***	4.04***	3.43**
	[1.09]	[1.19]	[1.22]	[1.06]	[1.11]	[1.61]
Household income (log)	-2.60***	-0.70	-2.54***	-2.43***	-1.44**	-1.56*
	[0.78]	[0.90]	[0.80]	[0.72]	[0.72]	[0.91]
Had private health insurance	-2.13	0.93	-1.68	-2.46*	-0.94	-1.69
	[1.35]	[1.49]	[1.49]	[1.31]	[1.34]	[1.90]
Lived in an owned home	5.08***	9.05***	4.78***	4.89***	7.54***	4.75**
	[1.29]	[1.43]	[1.41]	[1.26]	[1.32]	[1.99]
Mother employed	2.80**	7.48***	3.44**	2.98**	8.34***	6.49***
	[1.29]	[1.47]	[1.41]	[1.26]	[1.30]	[2.02]
Mother had depression	-2.37**	-3.98***	-1.95	-2.21**	-3.43***	-1.93
	[1.13]	[1.22]	[1.26]	[1.10]	[1.14]	[1.63]
Mother smoked	-7.37***	-7.36***	-6.84***	-7.23***	-7.20***	-8.58***
	[1.46]	[1.63]	[1.59]	[1.43]	[1.54]	[2.27]
Dental practitioner density	0.91	0.02	0.04***	0.04***	0.64	0.79
	[0.63]	[0.02]	[0.01]	[0.01]	[0.66]	[0.70]
Rho		-0.47***				
		[0.05]				
Observations	9,938	26,714	8,721	10,769	11,428	5,159

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), DoH (2019c) for uptake rates (measured on calendar year) from 2015 to 2018, and Medicare Statistics at the Department of Human Services (for total benefit paid). CY indicates Calendar Year and FY refers to Financial Year.

DATA AVAILABILITY STATEMENT:

This paper uses unit record data from the Longitudinal Study of Australian Children (LSAC). These data are proprietary and researchers wishing to use them must seek approval from the relevant institutions. Details about how to obtain the data can be found in http://growingupinaustralia.gov.au/.