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State dependence in immunization and the role of discouragement

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ABSTRACT

We investigate whether having a child immunized at a prior schedule *genuinely* increases the likelihood of vaccinating the child at the subsequent schedule. We use longitudinal data from the Growing Up in New Zealand study and apply a dynamic random-effects model that also controls for the initial immunization status. Prior to any covariate-adjusted estimations, our data shows that almost 96% of the children immunized at the previous schedule are also immunized at the subsequent schedule. In comparison, only 29% of children who were not immunized at the prior schedule receive immunization at the next milestone, thereby indicating an unadjusted state dependence in immunization of 67 percentage points (p.p.). Upon controlling for relevant covariates and unobserved heterogeneities, the genuine state dependence in immunization is, on average, estimated to be 20 p.p. Importantly, the magnitude of the state dependence is greater for Māori (by 5 p.p.) and also greater for mothers that report being discouraged from having their child immunized during the antenatal period (by 10 p.p.).

1. Introduction

The long-term benefits of vaccination on child health and mortality are well-documented in the medical literature (Gust et al., 2004). However, despite the extensive evidence on the apparent positive health implications of immunization, under-immunization among children has risen over the past few decades (Gangarosa et al., 1998; Daley et al., 2021). This growth in under-immunization has, therefore, underscored the importance of identifying strategies that could encourage the uptake of routine childhood immunizations. In this study, we employ rich survey data on child immunization uptake in New Zealand to explore whether prior experiences of having a child immunized *genuinely* influence future immunization decisions. This might be particularly relevant for parents who are reluctant or undecided about vaccinating their child. To put it differently, a positive parental experience when the child received the vaccine might encourage them to undertake future immunizations.

Current health policy in New Zealand (NZ) focuses on promoting equitable access for child healthcare services. These services include free national immunization schedule vaccines and dental care for all children under 18 and cost-free doctor visits for all children under 14.[1] However, the country has inadequate vaccine coverage along with noticeable ethnic differences in healthcare utilization and health outcomes (Grant et al., 2009; Hobbs et al., 2017; Sinclair and Grant, 2021). Lack of accessibility to health services, insufficient funds of healthcare, and parental concern over vaccine safety are some of the key barriers to childhood immunization in NZ (Petousis-Harris, 2004; Lee and Sibley, 2020). As far as uptake is concerned, recent evidence further indicates that childhood immunization rates also vary by socio-economic conditions, demographic characteristics, residential location and parental availability as they juggle between several responsibilities (Walker et al., 2019; Lewycka et al., 2023).

Unlike the well-documented evidence on the socio-economic and institutional constraints to effective childhood immunization, there are not many empirical analyses on identifying pathways navigating to increased childhood immunization, especially in the NZ context. To that end, our analysis aims to understand whether uptake of childhood immunization at a prior schedule enhances the likelihood of children being immunized at the subsequent schedule. We utilize rich data from the Growing Up in New Zealand (GUiNZ) survey, which longitudinally tracks the development of slightly over 6800 Kiwi children. The survey holds a wide range of antenatal and postnatal information, both on the

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[1] See information in NZ government's "Free health services for children". Accessed from https://www.govt.nz/browse/health/free-health-services-for-children/immunise-your-child-for-free/ on November 18, 2022.

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child as well as on the family level. The wide range of antenatal information documented in the survey incorporates relevant data on maternal intention to immunize her child or whether the mother has received any information discouraging her from immunizing her child during the post-birth years. The GUiNZ dataset also provides a rich set of information on the mothers' background, including health, age, ethnicity, financial and educational traits. Therefore, the survey allows us to control for some of the important characteristics that are found to be associated with uptake of childhood immunization. The postnatal surveys provide information on whether the children were immunized at various standard immunization schedules, including 6 weeks, 3 months, 5 months, 15 months, and 48 months.

In the empirical literature, state-dependent models are estimated to assess whether "individuals who have experienced an event in the past are more likely to experience the event in the future than are individuals who have not experienced the event" (Heckman, 1981a). When analyzing state dependence in any outcomes, Heckman (1981a) highlights the relevance of two particular considerations. They are:

1. Prior exposure to an event has a genuine behavioural effect on a person–a person who has not experienced that event would behave differently than someone with such an experience,
2. individuals differ in their unobservable characteristics, which are persistent over time–and not properly controlling for them would lead to spurious state dependence.

The application of state-dependent models has been found across a number of domains, such as health and risky behaviours (e.g., self-assessed indicators, smoking behaviour), unemployment, and labour force participation. In our context, we follow Skrondal and Rabe-Hesketh (2014) and Wooldridge (2005) by using a dynamic model for binary data to isolate the genuine effect of having the child immunized on the likelihood of future immunization from a spurious relationship. The challenge in estimating longitudinal dependence in vaccination is that there are three potential factors that influence the decision: past immunization (state dependence), individual-specific time-invariant differences (unobserved heterogeneity), and–particularly relevant in short panels (Arulampalam and Stewart, 2009)–the effect of the initial response (initial conditions problem). For this reason, we apply a dynamic random-effects probit model. The model includes the lagged dependent variable to measure state dependence in immunization. We add the immunization decision at the 6-week schedule as a covariate to address the initial conditions problem (see Wooldridge, 2005). Moreover, we add a random-effects error term to account for unobserved heterogeneity that is mother-child-pair-specific and invariant across the different immunization schedules.

Prior to our covariate-adjusted estimation, we explore our raw data to calculate the unadjusted state dependence in child immunization. We find that 95.6% of the children immunized at the prior schedule are also immunized at the subsequent schedule. However, conditional on not being immunized at the previous schedule, the share of children receiving immunization at the next schedule drops to 28.6%. Taking the difference of both the shares, the unadjusted state dependence in immunization comes to approximately 67 percentage points (p.p.).

Our maximum likelihood estimation results demonstrate the importance of controlling for the initial conditions problem and also reveal that mother-child-pair-specific and schedule-invariant differences have a significant impact. Furthermore, we see a considerable degree of state dependence in child immunization. After controlling for differences in observable and unobservable characteristics as well as for the immunization status at the first schedule, the likelihood to immunize a child at schedule j is, on average, 20.4 p.p. higher if the child was immunized at schedule $j - 1$ compared to when the child was not. For additional context, the genuine effect estimated in our analysis is about one third of the raw data state dependence of 67 p.p.

Moreover, focusing on different ethnic groups, we find larger state dependence in child immunization in Māori families (25 p.p.), especially when restricting the sample to mothers who, during their antenatal period, were either unwilling or unsure about their decision to immunize their children. When interacting the lagged dependent variable with a binary indicator, which takes the value 1 if the mother received discouraging information on child immunization during pregnancy and 0 otherwise, the extent of state dependence increases to 35 p.p.

The remainder of the paper is structured as follows: Section presents a brief discussion of relevant information on NZ's child healthcare services; Section 3 describes data and provides descriptive statistics; Section 3 highlights the empirical model; and Section 4 presents results. The last section provides concluding remarks.

2. Background

Children in NZ receive vaccinations according to the National Immunization Schedule (NIS), which includes a series of immunizations delivered between the ages of six weeks and 12 years.[2] In particular, the schedule is designed to provide vaccinations at the ages of six weeks, three months, five months, 12 months, 15 months, four years, and 11 or 12 years. The vaccinations in the NIS protect children against a wide range of diseases, including meningococcal, rotavirus, diphtheria, tetanus, pneumococcal, chicken pox, hepatitis B, measles, mumps, rubella, etc.[3]

The vaccinations listed on the NIS are publicly funded and are free for all individuals regardless of their citizenship status. However, despite government support, child immunization rates are usually lower than the herd immunity thresholds for some of the common vaccine-preventable diseases (Ministry of Health, 2020).[4] In the early 90 s, NZ was considered to have "mediocre immunization coverage" (Turner, 2012, p. 9), with less than 60% of children fully immunized by the time they turned two– and with even lower rates among Māori and Pasifika children (42%, resp. 45%) (Centre., 1992). From 2007, the share had steadily risen until it crossed the 90%-threshold in June 2011. Prior to the COVID-19 pandemic in Jan-Mar 2020, the proportion of children who were fully immunized by their 24-month birthday ticked up to 92%. However, the rise in the immunization coverage was disrupted by the pandemic resulting in a sharp drop in the share of immunization to 83% three years later in Jan-Mar 2023.

There are also substantial ethnic inequities in child immunization coverage in New Zealand. Over the three-year time period from Jan-Mar 2020 to Jan-Mar 2023, coverage among Māori dropped from 87% to 69% and among Pacific children from 95% to 81%. Importantly, immunization rates for children at 24 months is one of the Ministry of Health's high-level Health System Indicators that are monitored for the government's priority of improving child wellbeing. Furthermore, the full immunization coverage by the time babies approach their six-month birthday was even lower, with current rates as low as 47% for Māori and 60% for Pacific children. In comparison, the rate is roughly around 75% for NZ European babies.

Suboptimal immunization rates have both short- and long-term health implications (Doherty et al., 2016; Bloom et al., 2017). The

[2] See information in NZ Government's Health New Zealand's website. Accessed from https://www.tewhatuora.govt.nz/for-the-health-sector/vaccine-information/new-zealand-immunisation-schedule/ on July 17, 2023.

[3] There is no general structured alternative immunization in place when having an incomplete immunization history. However, it is recommended to plan a catch-up immunisation schedule to protect as soon as possible. Accessed from https://www.immune.org.nz/factsheets/catch-up-vaccinations-for-those-with-unknown-or-incomplete-immunisation-history#:~:text=Plan%20a%20catch%2Dup%20immunisation,protect%20as%20soon%20as%20possible.&text=Ensure%20a%20minimum%204%2Dweek,at%20least%20six%20months%20apart. on November 1, 2023.

[4] For instance, the herd immunity threshold for measles is around 92–94%.

2019/20 measles outbreak in NZ demonstrated the impact of suboptimal coverage, with more than 2000 cases and 700 hospitalizations, and associated complications included cases of encephalitis and pneumonia among young children (Ministry of Health, 2020; Turner, 2019). The measles outbreak also exacerbated pre-existing inequities as Māori and Pacific populations were disproportionately impacted, with the highest rates of measles and hospitalizations (Sonder and Ryan, 2020). To increase the uptake of childhood vaccinations and encourage catch-up immunization, investing in outreach programs and vaccine campaigns, engagement with parents and promoting public awareness, and extending support and developing collaboration with local health service providers are important (Turner, 2012; Hayman et al., 2017; Turner et al., 2017).[5]

In this study, we add to the existing empirical evidence by investigating whether a child's vaccination status at a previous schedule increases their chances of being immunized at subsequent schedules. As such, our analysis opens a broad scope for future research of identifying effective strategies that could increase state dependence in childhood immunization.

3. Data and descriptive statistics

We use data from Growing Up in New Zealand (GUiNZ) birth cohort to study state dependence in immunization. The GUiNZ is a child-focused longitudinal study and follows children from the antenatal stage until young adulthood. The aim of the survey is to understand the various pathways that affect a child's development. The study commenced in 2008 with the recruitment of 6822 pregnant mothers with an expected due date between March 2009 and May 2010. A cohort of 6822 children were born to the pregnant mothers recruited for the survey. Note that information is only collected for the child in the family who was born at that survey time and not for their siblings. Further details about recruitment, representativeness of the cohort to the population, etc., are provided by Morton et al. (2018).

The study currently consists of seven data collection waves (denoted as DCW), starting with DCW0 before the child is born (mostly represented by the last trimester of the mother's pregnancy) and reaching DCW6 when the child turns 72 months old. There are several contact points for the first two waves after the child is born (DCW1–2) to collect timely information on the child's development.

We are particularly interested in two sets of immunization-related information (see Fig. 1). First, the mothers' self-reported immunization status of the child.[6] The first wave after a child's birth (DCW1) includes information about the children from their birth until they are nine months old. The information in DCW1 is collected at several stages (six-weeks, 35-weeks, 9-months). In DCW1, the child's immunization status is provided for the schedules at: 6 weeks, 3 months, and 5 months. The subsequent wave (DCW2) covers the child's second year, and information is collected at 16 months, 23 months, and 2 years. The wave includes information on the child's 15-month immunization status. Next, the wave denoted as DCW5 holds information on the child's 48-month immunization status. In total, we have a maximum of five schedules for child's immunization status (6 weeks, 3 months, 5 months, 15 months, and 48 months).

The antenatal wave DCW0 holds a wide range of relevant information on the sample mothers and their children, potentially impacting the decision to immunize the child. Regarding mother's characteristics, we account for mothers' age,[7] whether the child was planned, indicator of the first-born child,[8] disability status, the relationship status,[9] ethnicity, highest education, household income, and the intention to immunize the child. Moreover, we include child's gender, which might also be linked to the parental decision to immunize (Tracey et al., 2022).

For our covariates, we only include individual-level information from the first wave of GUiNZ (DCW0) largely because not all variables are consistently defined and documented in the subsequent waves. We also excluded mothers with missing information to construct the final sample. Furthermore, as will be discussed in the next section, our empirical specification also requires us to consider those mother-child pairs whose information is available for the first three schedules. After that, while a mother-child pairs may drop out of the panel due to missing information, they cannot re-enter at a later immunization schedule. Finally, our analysis focuses on women with a singleton live-births to reduce unobserved heterogeneities that may arise from multiple births or pregnancy and birth-related complications.

Our final sample consists of 4771 mother-child pairs for the first three schedules, 4581 pairs for the fourth schedule and 4377 pairs for the last schedule. Therefore, our final unbalanced panel consists of 23,271 observations.

Column (I) of Table 1 displays the mother's characteristics for the sample from the antenatal survey. Columns (II)-(VI) show the distribution of the mother's antenatal characteristics for the sample of children who were immunized at different schedules starting from six weeks to 48 months. Although the descriptive information vary slightly by samples, the corresponding shares for each of the maternal characteristics largely remain comparable across different schedules. Comparing the sample from the antenatal survey to the sample from the 48-month schedule (column (VI)), a child is more likely to be vaccinated in the later schedule if: (i) they are the first-born (40.06% versus 41.96%), (ii) the child was planned (65.04% versus 67.46%), (iii) the mother's household income belonged to the top two income categories (47.64% versus 40.85%), (iv) the mother has a Bachelor's degree or a higher degree (43.48% versus 46.04%), (v) and the parent has intention to immunize the child (84.68% versus 86.97%). However, except for the intention to immunize the child, most differences in the distribution of the mother's antenatal characteristics and the maternal characteristics across different schedules who immunize their child are not statistically significant.

The rich information in the GUiNZ cohort includes data on whether the mother received encouragement or discouragement regarding immunizing their child during pregnancy. This information was

[5] Also see article published in NZ Herald. Accessed from https://www.nzherald.co.nz/nz/nzs-child-immunisation-rates-hit-record-lows-with-health-experts-petrified-of-measles-and-other-deadly-epidemics/KFGAQTTUJBPJ-BAO3NHPBSS4GAE/#:~:text=According%20to%20the%20Ministry's%20latest,83%20per%20cent%20of%20Pasifika%20 on July 21, 2023.

[6] In the first postnatal wave (DCW1), participants were linked with the National Immunization Register data to verify the 6-week, 3-month and 5-month immunizations. The overlap between self-reported and recorded immunizations is considerably high.

[7] We create a binary variable which takes the value 1 if the mother was aged 25 or below during the antenatal interview and 0 else.

[8] There is no further information on the birth order available. Moreover, there is no information on the immunization status of older siblings, which potentially can impact the mother's decision to immunize in the future.

[9] We create a binary indicator which takes the value 1 if the mother is married, cohabiting, or a couple but not living together and 0 if dating or not in a relationship.

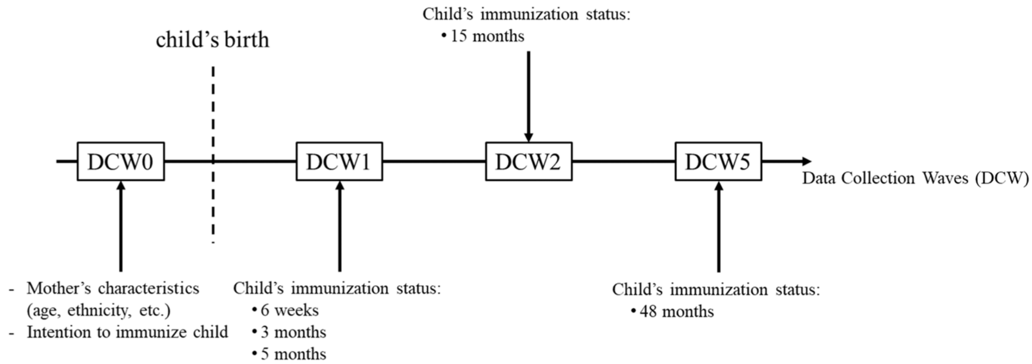

Fig. 1. Growing Up in New Zealand (GUiNZ) data structure. Note: Authors' visualization of the GUiNZ data preparation.

Table 1
Mother's characteristics and immunization behaviour (in %).

	Antenatal (I)	Child immunized at 6 weeks (II)	3 months (III)	5 month (IV)	15 month (V)	48 month (VI)
Aged 25 or below	19.15	19.45	19.27	19.10	18.70	17.95
Disability	5.96	5.90	5.88	6.00	5.97	5.66
First child	40.06	40.64	40.98	41.97*	41.11	41.96*
Child planned	65.04	65.12	65.29	65.80	65.77	67.46**
Boy	51.35	51.78	51.68	51.55	51.47	51.25
In a relationship	96.29	96.31	96.32	96.43	96.38	96.50
Household income						
≤$20k	3.64	3.64	3.63	3.64	3.38	3.23
$20k-$30k	5.17	5.18	5.22	5.12	4.94	4.79
$30k-$50k	13.17	13.07	13.02	12.87	12.61	12.05
$50k-$70k	16.73	16.52	16.45	16.39	16.22	15.38*
$70k-$100k	23.66	23.51	23.62	23.32	23.68	23.70
$100k-$150k	22.90	23.16	23.09	23.32	23.57	24.41
>$150k	14.74	14.92	14.98	15.35	15.60	16.44**
Highest education						
No sec education	4.86	4.91	4.88	4.66	4.57	4.21
NCEA 1–4	21.21	21.28	21.17	21.21	20.86	20.02
NCEA 5–6	30.46	30.20	30.27	29.97	30.08	29.73
Bachelor's degree	25.27	25.25	25.23	25.45	25.56	26.45
Higher degree	18.21	18.36	18.45	18.71	18.93	19.59
Self prioritized ethnicity						
NZ European	61.92	61.29	61.20	61.22	62.62	63.97*
Māori	12.48	12.52	12.41	11.61	12.21	11.46
Pasifika	11.64	11.91	12.03	12.05	11.38	10.67
Asian	13.96	14.28	14.35	15.11	13.79	13.90
Intention to immunize child						
Immunize	84.68	87.17***	87.43***	87.64***	87.37***	86.97***
No immunization	2.34	0.35***	0.29***	0.28***	0.23***	0.32***
Not decided yet	12.98	12.48	12.28	12.08	12.40	12.71
Share immunized	-	95.43	93.92	90.30	94.06	86.18
Sample[b]	4 771	4 553	4 481	4 308	4 304	3 772

Note: Using GUiNZ data and own calculations. Column (I) shows the mother's antenatal characteristics (the information on child's gender is retrieved from the first wave after birth). Columns (II)-(VI) refer to the mother's antenatal characteristics if their child was immunized at the respective schedule. Significance level of student *t-test* between Columns (II)-(VI) and Column (I): *** p<0.01, ** p<0.05, * p<0.1. Reading example: 19.15% (column (I)) of the mothers in the sample are aged 25 and below during the antenatal interview; however, only 17.95% (column (VI)) of the mothers aged 25 and below during the antenatal interview have their child immunized at the 48 month schedule.

captured in the antenatal wave (DCW0).

According to column (I) of Table 2, about 15% of mothers report receiving discouraging information before childbirth.[10] However, the ethnic differences are noticeable, with a much smaller share observed among Asian (column (V)) and Pasifika (column (IV)) mothers compared to those belonging to NZ European[11] (column (II)) and to Māori (column (III)) ethnicities. The bottom panel of Table 2 provides a preliminary understanding of how receiving discouraging information corresponds to actually immunizing the child. It shows that in total, 92% of the children receive immunization. Breaking it further down by ethnicity, we see that mothers belonging to NZ European and Māori

[10] The mothers are also asked about the source of discouraging information (multiple responses are possible): 50.79% listed family, whānau, and friends, 47.39% media including the internet, radio, TV, books, magazines, newspapers, and 25.83% medical professionals including GP (family doctor), midwife, obstetrician, dietician/nutritionist and alternative health practitioner.

[11] A *t-test* shows that Asian (*t*-stat=6.271, *p*-value=0.000) and Pasifika (*t*-stat=7.658, *p*-value=0.000) mothers have a statistically significantly lower share receiving discouraging information compared to NZ European but not Māori (*t*-stat=1.442, *p*-value=0.149).

Table 2
Discouraging information on immunization (in %).

	Full sample (I)	NZ European (II)	Māori (III)	Pasifika (IV)	Asian (V)
Received discouraging information before child birth					
Share	15.04	18.28	15.79	7.55	6.30
Individuals	4 771	2 954	595	556	666
Child immunized at *j*					
No discouraging information	93.41	92.62	90.81	95.28	97.16
Discouraging information	84.52	83.48	82.61	93.17	94.00
Total	92.07	90.96	89.54	95.12	96.96
t-test	18.13***	15.019***	5.28***	1.35	2.521**
(p-value)	(0.000)	(0.000)	(0.000)	(0.176)	(0.011)
Sample[a]	23 271	14 601	2 887	2 625	3 158

Note: Using GUiNZ data and own calculations. [a] multiple observations per individual. Significance level of student *t-test*: *** p<0.01, ** p<0.05, * p<0.1.

Table 3
Transition matrix of immunization (in %).

	immunized at j		
immunized at j-1	No	Yes	Total_{j-1}
No	71.41	28.59	6.57
	(81.64)	(18.36)	(14.28)
Yes	4.40	95.60	93.43
	(5.74)	(94.26)	(85.72)
Total_j	8.80	91.20	
	(16.58)	(83.42)	

Note: Using GUiNZ data and own calculations. Above numbers show the immunization status at schedule *j* differentiated by the immunization status at the previous schedule *j-1*. Reading example: 71.41% (28.59%) of the children who did not receive an immunization at schedule *j-1* did not (did) receive an immunization at schedule *j*. Numbers in parentheses refer to mothers receiving discouraging information before birth.

ethnicity have the lowest share of children receiving immunization (about 91% and 90%, respectively). Asian mothers have the highest share of children being immunized at any given time (97%). The immunization rates also differ by whether a mother was discouraged from having her child immunized. In general, the share of children having received an immunization is about 9 p.p. higher for mothers who did not receive any discouraging information than for those who did. The negative link between receiving discouraging information and child immunization outcomes also aligns with the findings in Lewycka et al. (2023). Table 2 also shows that the gap in immunization status between those who receive discouraging information versus those that don't is more prominent among NZ European and Māori compared to Pasifika and Asians. And except for Pasifika mothers, the difference in the immunization rate is statistically significant.

As explained earlier, this study aims to understand the intertemporal link in immunization, which means whether having the child immunized at the previous schedule *genuinely* affects the likelihood of vaccinating the child at the following schedule. We start with constructing a transition matrix for the child's six immunization milestones. The idea is to show the distribution of the immunization status at milestone t conditional on the immunization status at the previous milestone $t-1$. The main diagonal of Table 3 shows that most children who were immunized at t were already vaccinated at t-1 (96%). Additionally, a majority of children who are not immunized at the previous schedule appear to remain non-immunized in the subsequent schedule (71%). Only a small fraction of those who received immunization at the previous milestone did not receive one at the subsequent schedule (4%). But we see a higher share when looking at the percentage of children who did not receive immunization at the prior schedule but did in the following schedule (29%). Unsurprisingly, when restricting the sample to mothers who received discouraging information before childbirth (numbers in parenthesis of Table 3), persistence in non-immunization is substantially higher.

Table 3 also suggests that having a child immunized at the previous milestone plays a significant role in the likelihood of having the child immunized at the subsequent schedule: the raw data state dependence is 67 p.p. (95.60%−28.59%). However, the decision to immunize one's child might not only depend on past experience (e.g., Table 3), but observable characteristics (e.g., Table 1) and unobservable attributes, which might be individual-specific and time-invariant. In the following section, we will introduce the econometric model, which takes all three aspects into account.

4. Empirical strategy

The underlying concept of our empirical model is that the past outcome has a genuine impact on the current outcome. This type of model has been applied in various contexts, including labour (e.g., Stewart, 2007; Ayllón et al., 2022), health (e.g., Clark and Etilé, 2006; Haan and Myck, 2009), education (e.g., Miranda, 2011), or poverty (e.g., Biewen, 2009; Devicienti and Poggi, 2011). By extending the application of state-dependent models to our current research objective, we seek to understand whether having one's child immunized influences the likelihood to immunize the child at the next schedule. The starting point is the following reduced form model on the decision to immunize:

$$y_{ij} = \mathbf{1}\left(\beta y_{i(j-1)} + X_{i,0}^{'}\rho + \nu_{ij} > 0\right) \tag{1}$$

where the subscript $i = 1, \ldots, N$ indexes mother-child pairs and the subscript $j = 1, \ldots, J$ indexes the different stages of the immunization schedule, spanning from 6 weeks ($j = 1$) to 48 months ($j = 5$).[12] y_{ij} is a binary indicator variable taking the value 1 if the child i was fully or partially[13] immunized at schedule j and 0 else. We assume that the decision to immunize is influenced by whether the child was immunized at the previous schedule $y_{i(j-1)}$ and observable characteristics represented by the vector of explanatory variables $X_{i,0}^{'}$. As already highlighted, due to the data structure, we included the observable characteristics from the antenatal wave (see Table 1).

Further, we also included an idiosyncratic shock $\nu_{ij} \sim N(0, \sigma_\nu^2)$. It is possible that the mother-child pairs not only differ in their observable characteristics but might have differences in unobservable attributes that are constant across the different schedules. Therefore, by further decomposing the idiosyncratic shock of Eq. (1) into two uncorrelated terms represented by a schedule-invariant mother-child-pair-specific random effect and an error term, ν_{ij} takes the following form:

$$\nu_{ij} = \alpha_i + u_{ij} \tag{2}$$

with $\alpha_i \sim N(0, \sigma_\alpha^2)$ and $u_{ij} \sim N(0, \sigma_u^2)$. One restriction is that α_i is not correlated with the observable characteristics. Mundlak (1978) and Chamberlain (1984) show that correlation between the random-effects and the observed characteristics is allowed when also controlling for the time means of the time-varying observable characteristics. However, in our setting this is not possible as the set of explanatory variables is not updated at each schedule and as the time gap is not equally spaced between the schedules.

Even though ν_{ij} are assumed independent and identically distributed (iid), because of the random-effects term α_i the composite error term is

[12] Following the suggestion of a referee, we do not use t as the second subscript as the time intervals are not equally spaced between the immunization schedules.

[13] Partial immunization refers to receiving some of the vaccinations at a scheduled milestone. Having a partial immunization in one time period does not impact the ability to receive full immunization at a later schedule.

correlated across schedules. The correlation is represented by:

$$corr(\nu_{ij}, \nu_{is}) = \lambda = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_u^2} \tag{3}$$

for $j, s = 1, \ldots, J$ and $j \neq s$.

Note that N is large but J is small and therefore asymptotics are on N alone. If the initial schedule is not believed to be exogenous, α_i is correlated with the outcome in $j = 1$, also known as the 'initial conditions problem' (Heckman, 1983b). There exist several methods to address the initial conditions problem. For example, Heckman (1983b) proposes specifying a linearized reduced form equation for the initial observation which includes exogeneous instruments. We follow the suggestions of Wooldridge (2005) by implementing a conditional maximum likelihood estimator. Arulampalam and Stewart (2009) and Rabe-Hesketh and Skrondal (2013) show that the conditional likelihood estimator produces unbiased estimators for $J \geq 3$:

$$\alpha_i = a_0 + a_1 y_{i,0} + \gamma_i \tag{4}$$

Here, $y_{i,0}$ refers to the immunization status in the initial schedule. Using Eq. (4), the Eq. (1) can be re-written as:

$$y_{it} = \mathbf{1}\left(\beta y_{i(j-1)} + X_{i,0}^{'}\rho + a_0 + a_1 y_{i,0} + \gamma_i + u_{ij} > 0\right) \tag{5}$$

Note that y_{ij} is binary and we chose as normalization $\sigma_u^2 = 1$. The outcome probability is:

$$P_{ij}(\gamma^*) = \Phi\left(\left(\beta y_{i(j-1)} + X_{i,0}^{'}\rho + a_0 + a_1 y_{i,0} + \sigma_\gamma \gamma^*\right)(2y_{ij} - 1)\right) \tag{6}$$

The respective likelihood function is:

$$L = \prod_{i=1}^{N} \int_{\gamma^*} \left\{ \prod_{j=1}^{J} P_{ij}(\gamma^*) \right\} \mathrm{d}F(\gamma^*) \tag{7}$$

with F being the distribution function of $\gamma^* = \gamma/\sigma_\gamma$ and $\sigma_\gamma = \sqrt{\lambda/(1-\lambda)}$. We assume that γ is normally distributed, and following Butler and Moffitt (1982), the integral over γ^* can be integrated out using Gaussian–Hermite quadrature. As the β-coefficient cannot be directly interpreted, we calculate the average partial effects.

Discouraging information To understand whether discouraging information during pregnancy could play a role in the state dependence in immunization, we adjusted Eq. (5) by interacting the lagged dependent variable with a dummy variable $D_{i,0}$ taking the value 1 if the mother received discouraging information antenatally and 0 otherwise:

$$y_{ij} = \mathbf{1}\Big(\beta_1\left(1 - y_{i(j-1)}\right)D_{i,0} + \beta_2 y_{i(j-1)}\left(1 - D_{i,0}\right) + \beta_3 y_{i(j-1)} D_{i,0} + X_{i,0}^{'}\rho + a_0 + a_1 y_{i,0} + \gamma_i + u_{ij} > 0\Big) \tag{8}$$

Note that the reference case is $\left(1 - y_{i(j-1)}\right)\left(1 - D_{i,0}\right)$, which is not having the child immunized at the previous schedule and having not received any discouraging information before the child's birth. Thus, β_1 refers to the effect of not having immunized the child and having received discouraging information, β_2 measures the effect of when child was immunized but the mother did not receive any discouraging information, and β_3 refers to the effect of when child was immunized and the mother received discouraging information.

5. Results

Our empirical model controls for differences in observable characteristics obtained from the antenatal interview, the immunization status at the previous schedule, the immunization status at the 6-week schedule, and unobserved heterogeneity. The maximum likelihood estimation results for our basic specification can be found in Table 4. Regarding observable characteristics, we observe that the indicators of being the first child and whether the child was planned are positively and significantly associated with the likelihood of the child being immunized. Moreover, we can detect significant ethnic differences. As such, we also apply ethnicity-specific estimations. There is a strong impact associated with the antenatal intention to immunize one's child, with the largest negative effect being found in the event when mothers do not have the intention to immunize the child. No significant effects are found for age, household income, educational background, child's gender, the mother's relationship status or disability status.

We also find a strong impact of the initial immunization status, indicating that having the child immunized at the 6 weeks milestone itself significantly elevates the likelihood of immunizing the child at the follow-up milestones. Finally, the value of $\hat{\lambda} = 0.12$ implies that the mother-child-pair-specific schedule-invariant error term contributes about 12% to the composite variance. Not controlling for unobserved heterogeneity would cause a biased estimation of β, resulting in overstating the state dependence.

Table 5 presents the average partial effects of our lagged dependent variable. The results show that in the pooled sample (column (I), top panel), having a child immunized at the previous schedule $\left(y_{i(j-1)} = 1\right)$ increases the likelihood of having the child immunized at the next schedule by, on average, 20.4 p.p. compared to those who are not immunized in the previous schedule $\left(y_{i(j-1)} = 0\right)$. The raw data state dependence is 67 p.p.; thus, about one third is explained by genuine state dependence, highlighting the importance to control for observed and unobserved characteristics. When we apply ethnicity-specific estimations, we find greater levels of state dependence among Māori (column (III), top panel) compared to the other ethnic groups.

Table 4
Maximum-likelihood estimates of Eq. (5).

	Coef.	Std. Err.
Aged 25 or below	-0.062	0.050
Child a boy	-0.046	0.036
Disability	0.004	0.075
First child	0.355***	0.045
Child planned	0.135***	0.041
Mother in a relationship	-0.009	0.094
Household income		
≤$20k	Reference	
$20k-$30k	0.040	0.124
$30k-$50k	-0.052	0.108
$50k-$70k	-0.082	0.107
$70k-$100k	-0.041	0.106
$100k-$150k	-0.029	0.108
>$150k	0.136	0.116
Highest education		
No sec education	Reference	
NCEA 1–4	-0.028	0.085
NCEA 5–6	0.006	0.083
Bachelor's degree	-0.027	0.089
Higher degree	0.027	0.094
Self-prioritized ethnicity		
NZ European	Reference	
Māori	-0.175***	0.052
Pasifika	0.187***	0.064
Asian	0.394***	0.069
Intention to immunize child		
Immunize	Reference	
No immunization	-1.327***	0.140
Not decided yet	-0.389***	0.055
Immunized_{j-1}	1.134***	0.091
Immunized_0	1.463***	0.133
$\hat{\lambda}$	0.120***	0.038
Log likelihood	-3 493.920	
Sample	23 306	

Note: Using GUiNZ data and own calculations. Significance level: *** p<0.01, ** p<0.05, * p<0.1. Coefficients are estimated using the dynamic random-effects probit models described in Eq. 5.

Table 5
Estimated state-dependence effect – average partial effects.

	Full sample (I)	By mother's ethnicity: NZ European (II)	Māori (III)	Pasifika (IV)	Asian (V)
Sample: Basic specification					
Average partial effects	0.204***	0.189***	0.253***	0.207***	0.209***
	(0.033)	(0.042)	(0.070)	(0.112)	(0.073)
Log likelihood	-3 493.920	-2 152.626	-684.929	-353.485	-253.031
Raw data state dependence	0.670	0.737	0.470	0.461	0.522
Individuals	4 771	2 954	595	556	666
Sample: w/o intent to immunize					
Average partial effects	0.217***	0.202***	0.347***	-	-
	(0.072)	(0.083)	(0.128)		
Log likelihood	-634.091	-475.956	-109.218		
Raw data state dependence	0.827	0.844	0.687		
Individuals	732	574	81		
Sample: Mother aged 25 or below					
Average partial effects	0.137***	0.131**	0.152**	-0.005	0.038
	(0.036)	(0.051)	(0.068)	(0.049)	(0.067)
Log likelihood	-707.183	-322.272	-221.620	-90.274	-40.490
Raw data state dependence	0.538	0.649	0.374	0.335	0.336
Individuals	904	407	212	154	81

Note: Using GUiNZ data and own calculations. Average partial effects are estimated using the dynamic random-effects probit models described in Eq. (5), with standard errors in parenthesis and significance level: *** p<0.01, ** p<0.05, * p<0.1. Three different samples are analysed: basic specification (top panel), mothers who state before the child's birth that they have not decided yet or do not want to have their child immunized after birth (middle panel), and mothers who were mothers who are 25 years old or younger in the antenatal wave (bottom panel). Covariates included (but not shown here) are those listed in Table 1. The raw data state dependence refers to the difference (in percentage points) in the share of children immunized at schedule *j* and being immunized at *j-1* compared to the share of children immunized at schedule *j* and not being immunized at *j-1*.

As Table 5 shows, the intention to immunize a child is strongly associated with the child being vaccinated after they are born. However, when we restrict the sample to those mothers who state before the child's birth that they have not decided yet or do not want to have their child immunized after birth (see medium panel of Table 5), the average size of the state dependence hardly changes. Thus, the experience of having a child immunized genuinely elevates the likelihood of immunizing the child at the next schedule. This seems to hold true, especially for mothers who identify themselves as Māori, though the sample size is much smaller than the total sample size.

We further explore whether a mother's age affects state dependence on immunization. For this, we reduced our sample to mothers who are 25 years old or younger. The bottom panel of Table 5 shows that state dependence drops noticeably, and the likelihood of immunizing the child at *j* increases by, on average, 13.6 p.p. if the child was immunized at the previous schedule compared to if they were not. Our findings indicate that state-dependence in child immunization is likely to vary by mothers' age.

Discouraging information In Table 2, we present descriptive evidence that receiving discouraging information during pregnancy about immunizing the child once they are born can harm the likelihood of having the child immunized at the next schedule. For this reason, we extended our basic specification by interacting the lagged dependent variable with a binary indicator $D_{i,0}$ which takes the value 1 if the mother received such information and 0 else. Table 6 shows the respective average partial effects, both for the full sample (column (I)) as well as for within each ethnic group (columns (II)-(V)).

As the reference category, we consider the mother-child combination in which the mother did not receive any discouragement and the child is not immunized at the prior schedule. Relative to the reference category, if the mother has received discouraging information and child was not immunized in the previous schedule $j-1$, the likelihood of having the child immunized at the next schedule *j* drops by, on average, 9.9 p.p. However, if the mother has immunized the child at $j-1$, mothers are significantly more likely to have their child immunized at the subsequent schedule, regardless of whether she was discouraged to immunize her child during her pregnancy. The effects are statistically significant at the 1% level. This finding is also relatively stable across ethnicity.

6. Conclusion

The primary objective of our study is to examine whether having a child immunized at a prior schedule *genuinely* influences the likelihood of vaccinating the child at the following schedule. We use birth cohort data from the GUiNZ study, which tracks the lives of close to 7000 Kiwi children. The longitudinal aspect of the survey, along with extensive information on child development and family background, supports our analysis. Importantly, this data provides immunization status across various schedules, including at 6 weeks, 3 months, 5 months, 15 months

Table 6
Mother received discouraging information before childbirth[a].

	Full sample (I)	NZ European (II)	Māori (III)	Pasifika (IV)	Asian (V)
Average partial effects					
$\left(1-y_{i(j-1)}\right)\left(1-D_{i,0}\right)$	*reference category*				
$\left(1-y_{i(j-1)}\right)\ D_{i0}$	-0.099***	-0.089**	-0.109	-0.069	-0.166
	(0.034)	(0.042)	(0.085)	(0.201)	(0.227)
$y_{i(j-1)}\left(1-D_{i,0}\right)$	0.193***	0.173***	0.246***	0.206**	0.195***
	(0.030)	(0.041)	(0.072)	(0.112)	(0.073)
$y_{i(j-1)}D_{i,0}$	0.177***	0.159***	0.202***	0.210**	0.183**
	(0.031)	(0.041)	0.075	(0.115)	(0.074)
Log likelihood	-3 481.214	-2 143.713	-681.506	-353.402	-252.175
Raw data state dependence	0.670	0.737	0.470	0.461	0.522
Individuals	4 771	2 954	595	554	657

Note: Using GUiNZ data and own calculations. $y_{i(j-1)}$ indicates whether the child was (=1) or was not (=0) immunized at the previous schedule. D_i indicates whether the mother received antenatal discouraging information on immunizing the child (=1) or else (=0). Each column refers to a separate maximum likelihood estimation using the dynamic random-effects probit models described in Eq. 8, with standard errors in parenthesis and significance level: *** p<0.01, ** p<0.05, * p<0.1. Covariates included (but not shown here) are those listed in Table 1. The raw data state dependence refers to the difference (in percentage points) in the share of children immunized at schedule *j* and being immunized at *j-1* compared to the share of children immunized at schedule *j* and not being immunized at *j-1*.

and 48 months.

Additionally, we employ a dynamic random-effects probit model to identify the genuine impact of having the child immunized on the likelihood of the subsequent immunization schedule. Our identification strategy also controls for the initial conditions problem (the effect of the first decision) and mother-child-pair-specific schedule-invariant differences.

It is also important to note that while our dynamic random effects specification follows a standard approach commonly adopted in the extant literature, the empirical validity of the specification relies on the assumption that individuals' unobserved traits are uncorrelated with observable characteristics. Concerns related to possible confounding influences of unaccounted individual-level information could be partially addressed by employing a Mundlak-Chamberlain decomposition (Mundlak, 1978), which cannot be implemented in this context.

Nonetheless, the key finding is that of strong state dependence in child immunization outcomes. In particular, after controlling for differences in observable and unobservable characteristics as well as the initial immunization, we find that the likelihood to immunize a child is, on average, 20.4 p.p. higher at schedule j if the child was immunized at the prior schedule $j-1$ compared to if not.

There are some important ethnic differences in this result, with state dependence playing a larger role for Māori, and when we restrict the sample to mothers who stated before the child's birth that they do not want or do not know yet whether they want to immunize their child. The strong state dependence result for Māori in particular stands out in terms of policy implications, given the persistent ethnic disparities in childhood immunization coverage for Māori, relative to NZ European over time, with a worsening situation during the COVID-19 pandemic.

One limitation of the survey is the limited information on the immunization status of siblings, which might also impact the parental decision. The Ministry of Health's National Immunization Register holds information on the immunization status of all NZ children and opens up potential scope for future research to explore further and verify our survey-based analysis using administrative data.

CRediT authorship contribution statement

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Data availability

The data that has been used is confidential.

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