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State Dependence in Immunization and the Role of Discouraging Information*

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Abstract

Does having a child immunised at the prior schedule *genuinely* impact the likelihood of vaccinating the child at the following schedule? Using longitudinal data from Growing Up in New Zealand study, we apply a random-effects probit model that also controls for the initial immunisation status. We detect sizeable state dependence in immunisation, indicating that the likelihood of a child increases, on average, by 21 percentage points if the child was immunised at the previous schedule compared to if not. This effect is further exacerbated if the mother received antenatal discouraging information on immunisation.

Keywords: State dependence, vaccination, random-effects, initial conditions problem
JEL-Code: I12; I18; C33

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1. Introduction

The benefits of vaccination on child health and mortality are clear as it substantially lowers the number of vaccine-preventable diseases (Gust et al., 2004). Even though the positive effects of immunization are apparent and proven in numerous studies, under-immunization among children has increased in the past decades (Gangarosa et al., 1998). There are multiple reasons for this development, including vaccine safety concerns (Chen, 1999; Taylor et al., 1999), or parents' attitudes, beliefs, and behaviors (Gust et al., 2004). Further, the COVID-19 pandemic also caused a marked decrease in childhood immunisation coverage globally (Shet et al., 2022), driven in part by greater parental vaccine hesitancy (He et al., 2022).

In this study, we analyse whether the experience of having their child immunised genuinely impacts future immunisation decisions. This might be particularly relevant for parents who are reluctant or undecided about vaccinating their child–a positive parental experience when the child received the vaccine might encourage them to undertake future immunisations.

In our empirical study, we rely on New Zealand data. In the early 90s, New Zealand had a "mediocre immunization coverage" (Turner, 2012, p. 9), with less than 60% of children fully immunised by 2 years of age–and with even lower rates among Māori and Pasifika children (42%, resp. 45%) (Centre., 1992). Since 2007, the number was steadily rising and crossed the 90% threshold in June 2011. Since then, the number has moved sideways, sitting at 91.7% in March 2020. However, with the pandemic, the numbers dropped again and are now (March 2022) seven percentage points lower than two years ago (84.7%). This is well below the 92% target, and ethnic inequities in immunisation coverage persist.

Our study uses the Growing Up in New Zealand (GUiNZ) dataset, which tracks the lives of more than 6 000 Kiwi children. It holds a rich range of ante- and postnatal information, both on the child as well as on the parental level. This includes ante-natal information such as whether the mother decided to immunise the child or whether she has received or been told any information discouraging her from immunising the child once s/he is born. The GUiNZ dataset also provides rich information on the mother's background, including health, age, ethnicity, financial and educational background. Postnatal information helps us to determine whether the child was immunised at the various schedules, including at 6 weeks, 3 months, 5 months, 15 months, and 48 months.

The statistical phenomena whereby "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, 1981, p. 91) has been

explored in a number of domains, such as accidents, unemployment, or labour force participation. (Heckman, 1981) puts forward two reasons behind this phenomena:

1. the experience has *genuine* behavioural effect and an individual who has not experienced such an event would behave differently than someone with such an experience,

2. the individuals differ in their unobservable characteristics which are persistent over time–and not properly controlling for it would lead to *spurious* state dependence.

To separate the true/genuine from the spurious impact of having the child immunised on the likelihood of future immunisation, we follow Skrondal and Rabe-Hesketh (2014) and Wooldridge (2005) by using a dynamic model for binary data. The challenge in estimating longitudinal dependence in vaccination is that there are three potential factors that impact the decision: past immunisation (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 random-effects probit model that includes the lagged dependent variable and the immunisation decision at the 6-weeks schedule as covariates. We add as a further control variable the ante-natal decision on whether to vaccinate the child when born.

Our regression results show that it is crucial to control for the initial conditions problem and that individual-specific time-invariant differences have a significant impact. Furthermore, we see a considerable degree of state dependence: after controlling for differences in observable and unobservable characteristics as well as for the immunisation status at the first schedule, the likelihood to immunise a child is, on average, 21 percentage points higher if the child was immunised at $t-1$ compared to if not. Moreover, we find that state dependence plays a larger role among Māori, especially when restricting 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 immunise their child when s/he is born. When interacting the lagged dependent variable with a binary indicator which takes the value 1 if the mother received antenatal discouraging information on immunisation and 0 else, the spread in state dependence is further exacerbated.

The remainder of the paper is structured as follows: Section 2 describes data and provides descriptive statistics, Section 3 highlights the empirical model, and

Section 4 presents results. The last section concludes.

2. Data and Descriptive Statistics

We use data from Growing Up in New Zealand (GUiNZ) birth cohort to study state dependence in immunisation. It is a child-focused longitudinal study and follows children from before birth until young adulthood. The aim is to understand which pathways impact child's development. The study was commissioned by the New Zealand government in 2004 and commenced in 2008 with the recruitment of 6 822 pregnant mothers with an expected due date between March 2009 and May 2010. A cohort of 6 846 children were born into the cohort. In our study, we focus on women with a singleton life-birth.

The study currently consists of seven data collection waves (DCW), starting with DCW0 before the child is born (most often in 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 was born (DCW1-2) to collect timely information on the child's development.

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

DCW0 furthermore holds a range of individual- and household related information which potentially have an impact on the decision to immunise the child, including the mother's age, whether the child was planned, whether it is the first child, disability status, ethnicity, highest education, household income, and the intention to immunise the child. We do not include information from later waves

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

Table 1: Mother's characteristics and immunisation behavior

	Child immunised[a]	
	No	Yes
Age	31.28	30.70
Disability	6.54	5.91
First child	26.23	41.30
Child planned	60.25	65.82
Household income		
≤$20k	3.52	3.51
$20k-$30k	4.81	5.06
$30k-$50k	14.76	12.74
$50k-$70k	20.88	16.21
$70k-$100k	25.37	23.56
$100k-$150k	20.06	23.50
>$150k	10.60	15.42
Highest education		
No sec education	5.19	4.66
NCEA 1-4	21.25	20.93
NCEA 5-6	33.69	30.06
Bachelor's degree	25.04	25.55
Higher degree	14.82	18.80
Self prioritised ethnicity		
NZ European	71.50	61.98
Māori	16.39	12.09
Pasifika	6.92	11.64
Asian	5.19	14.29
Intention to immunise child		
Immunise	52.41	87.30
No immunisation	26.61	0.29
Not decided yet	20.98	12.40
Sample[b]	1 849	21 457

Note: Using GUiNZ data and own calculations. Mother's characteristics are collected at the antenatal wave DCW0. [a] Refers to the 6 week, 3 month, 5 month, 15 month, and 48 month immunisation schedule. [b] multiple observations per individual.

Table 2: Discouraging information on immunisation

	Full sample	NZ European	Māori	Pasifika	Asian
Received discouraging information before child birth					
Share	15.05	18.28	15.77	7.55	6.30
Individuals	4 778	2 958	597	556	667
Child immunised at *t*					
No discouraging information	93.41	92.62	90.83	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
Sample[a]	23 306	14 621	2 897	2 625	3 163

Note: Using GUiNZ data and own calculations. [a] multiple observations per individual.

because (i) not all variables are consistently defined across the waves, and (ii) information is only available for the respective wave but not for the immunisation time point. For our final sample, we drop mothers with missing information. Our final sample consists of $N = 4\,778$ mothers.

Table 1 displays the mother's antenatal characteristics, differentiated by whether the child was immunised at the different schedules. Considerable heterogeneity is visible, and a child is more likely to be vaccinated if: (i) it is the first child, (ii) the child was planned, (iii) the mother's household income belonged to the top two category, (iv) has a higher educational background, (v) identifies as Asian or Pasifika, (vi) and has the intention to immunise the child.

The rich information in the GUiNZ cohort includes data on whether the mother received encouragement or discouragement regarding immunising their child during. This information was captured in the antenatal wave (DCW0). According to Table 2, about 15% of mothers report receiving discouraging information before childbirth. However, the ethnic differences are stark, with a much smaller share among Asian and Pasifika compared to NZ European and Māori. The bottom panel of Table 2 provides a preliminary understanding of how receiving discouraging information corresponds to actually immunising the child. It shows that 92% of the children receive immunisation. Breaking it further down reveals heterogeneity by ethnicity, with NZ European and Māori having the lowest share (about 90%) and Asian having the highest (97%). The immunisation rates also differ when looking at discouraging information. In general, the share of children having received an immunisation is about 10 percentage points higher when having not received discouraging information compared to having received dis-

Table 3: Transition matrix of immunisation

	immunised at t		
immunised at $t-1$	No	Yes	Total_{t-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_t	8.80	91.20	
	(16.58)	(83.42)	

Note: Using GUiNZ data and own calculations. Numbers in parenthesis refer to mothers receiving discouraging information before birth.

couraging information. The negative link between receiving discouraging information and child immunisation outcomes also aligns with the findings in (Clark et al., 2020). As Table 2 also shows the gap in immunisation 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.

As explained earlier, this study aims to understand the inter-temporal link in immunisation, which means whether having the child immunised at the previous schedule *genuinely* impacts the likelihood for vaccinating the child at the following schedule. We start with constructing a transition matrix for the child's six immunisation milestones. The idea is to show the distribution of the immunisation status at milestone t conditional on the immunisation status at the previous milestone $t-1$. The main diagonal of Table 3 shows that most children who were immunised at t already were vaccinated at $t-1$ (96%)–and vice versa for those not immunised (71%). Only a small fraction who received immunisation at the previous milestone do not receive one at the proceeding one (4%), but the opposite case is much more prevalent (29%). Unsurprisingly, when restricting the sample to mothers who received discouraging information before childbirth (numbers in parenthesis of Table 3), persistence in non-immunisation is substantially higher.

However, the decision to immunise one's child might not only depend on observable characteristics (e.g., Table 1) or past experience (e.g., Table 3) but also on unobservable characteristics, 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.

3. Empirical identification strategy

The underlying thought of the 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). Translated into our research aim, we seek to understand whether having one's child immunised influences the likelihood to immunise the child in the future. The starting point is the following dynamic reduced form model on the decision to immunise:

$$y_{it} = 1\Big(\beta y_{i(t-1)} + X'_{i(t=-1)}\gamma + \nu_{it} > 0\Big) \tag{1}$$

where $i = 1,\ldots,N$ refers to the mother and $t = 1,\ldots,5$ to the time of immunisation. y_{it} is a binary variable taking the value of 1 if mother's i child was fully or partially immunised at t and 0 else. We assume that the decision to immunise is influenced by whether the child was immunised at the previous schedule $y_{i(t-1)}$ and some observable characteristics $X'_{i(t=-1)}$. Due to the nature of our panel, we only include the mother's characteristics which refer to the ante-natal wave (see Table 1.

Further, we also include an idiosyncratic shock $\nu_{it} \sim N(0,\sigma^2_\nu)$. However, mother's not only differ in their observable characteristics but there might also be unobservable heterogeneity which are constant over time. We assume that these are not correlated with mother's characteristics and the error term takes the following form:

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

with $\alpha_{it} \sim N(0,\sigma^2_\alpha)$ and $u_{it} \sim N(0,\sigma^2_u)$. This implies that because of the individual-specific time-invariant error term α_i the composite error term is correlated over time with

$$corr(\nu_{it},\nu_{is}) = \lambda = \frac{\sigma^2_\alpha}{\sigma^2_\alpha + \sigma^2_u} \tag{3}$$

for $t,s = 1,\ldots,T$ and $t \neq s$.As the individual-specific random-effects is constant over time, it is correlated with the outcome in the initial period $t = 1$. 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 low bias when the number of time periods is four or greater:

$$\alpha_i = a_0 + a_1 y_{i(t=0)} + \gamma_i \tag{4}$$

Here, $y_{i(t=0)}$ refers to the immunisation status in the initial schedule. Inserting Eq (4) into Eq (1) leads to:

$$y_{it} = 1\Big(\beta y_{i(t-1)} + X'_{i(t=-1)}\gamma + a_0 + a_1 y_{i(t=0)} + \gamma_i + u_{it} > 0\Big) \tag{5}$$

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

$$P_{it}(\gamma^*) = \Phi\Big([\beta y_{i(t-1)} + X'_{i(t=-1)}\gamma + a_0 + a_1 y_{i(t=0)} + \sigma_\gamma \gamma^*)(2y_{it} - 1)\Big] \tag{6}$$

The respective likelihood function is:

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

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 can not be directly interpreted, we calculate the average partial effects as. Note that due to the different normalization of the variances of probit models and random-effect probit models, we follow Arulampalam (1999) by adjusting our estimates:

$$\begin{aligned} PE_i = &\Phi\Big(\Big[\hat{\beta} + X'_{i(t=-1)}\hat{\gamma} + \hat{a}_0 + \hat{a}_1 y_{i(t=0)}\Big]\Big[\sqrt{1-\hat{\lambda}}\Big]\Big) - \\ &\Phi\Big(\Big[X'_{i(t=-1)}\hat{\gamma} + \hat{a}_0 + \hat{a}_1 y_{i(t=0)}\Big]\Big[\sqrt{1-\hat{\lambda}}\Big]\Big) \end{aligned} \tag{8}$$

Discouraging information To understand how discouraging information can impact state dependence in immunisation, we adjust Eq (5) by interacting the lagged dependent variable with a dummy variable D_i taking the value of 1 if the mother received before childbirth discouraging information and 0 else:

$$y_{it} = 1\Big(\beta_j y_{i(t-1)} \times D_i + X'_{i(t=-1)}\gamma + a_0 + a_1 y_{i(t=0)} + \gamma_i + u_{it} > 0\Big) \tag{9}$$

with $j \in \{1,\ldots,3\}$. Note that the reference category is not having the child immunised in the previous period $(y_{i(t-1)} = 0)$ and having not received any discouraging information $(D_i = 0)$. Thus, β_1 refers to having not immunised the child and having received discouraging information, β_2 when child was immunised and having not received discouraging information, and β_3 when child was immunised and having received discouraging information. The partial effects are calculated accordingly:

$$\begin{aligned} PE_i = &\Phi\Big(\Big[\hat{\beta}_j + X'_{i(t=-1)}\hat{\gamma} + \hat{a}_0 + \hat{a}_1 y_{i(t=0)}\Big]\Big[\sqrt{1-\hat{\lambda}}\Big]\Big) - \\ &\Phi\Big(\Big[X'_{i(t=-1)}\hat{\gamma} + \hat{a}_0 + \hat{a}_1 y_{i(t=0)}\Big]\Big[\sqrt{1-\hat{\lambda}}\Big]\Big) \end{aligned} \tag{10}$$

4. Results

Our empirical model controls for differences in observable characteristics at the antenatal interview, the lagged immunisation status, the immunisation status at the initial period, and unobserved heterogeneity. The regression results for our basic specification can be found in Table 4. Concerning observable characteristics, we can see that when it is the first child or when the child was planned has a significant positive impact on the likelihood of being immunised. Moreover, we can detect significant ethnic differences, and thus we also run ethnic-specific regressions. There is a strong impact associated with the antenatal intention to immunise one's child, with the largest negative effect when not planning to immunise the child. No significant impact is found for age, household income, educational background or disability status.

Furthermore, we find a strong impact of the initial immunisation status, indicating that having the child immunised at the 6 weeks milestone itself significantly elevates the likelihood to immunise the child at the follow-up milestones. Finally, $\hat{\lambda} = 0.12$ means that the individual-specific time-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 effect of state dependence.

Table 5 presents the average partial effects of our lagged dependent variable. It shows for our basic specification with the pooled sample that having a child immunised at the previous schedule $(y_{i(t-1)} = 1)$ increases the likelihood of having the child immunised at the next schedule by, on average, 20.9 percentage points compared to when having not the child immunised $(y_{i(t-1)} = 0)$. When we

Table 4: Regression results

	Coef.	Std. Err.
Age	0.017	0.033
Age squared	-0.000	0.001
Disability	0.005	0.075
First child	0.361***	0.047
Child planned	0.134***	0.042
Household income		
$\leq$\$20k	*reference*	
\$20k-\$30k	0.037	0.124
\$30k-\$50k	-0.055	0.108
\$50k-\$70k	-0.088	0.107
\$70k-\$100k	-0.049	0.106
\$100k-\$150k	-0.036	0.109
$>$\$150k	0.125	0.117
Highest education		
No sec education	*reference*	
NCEA 1-4	-0.028	0.086
NCEA 5-6	0.004	0.0842
Bachelor's degree	-0.032	0.090
Higher degree	0.024	0.0957
Self prioritised ethnicity		
NZ European	*reference*	
Māori	-0.171***	0.053
Pasifika	0.189***	0.064
Asian	0.395***	0.069
Intention to immunise child		
Immunise	*reference*	
No immunisation	-1.328***	0.141
Not decided yet	-0.388***	0.055
immunised_{t-1}	1.135***	0.091
$\text{immunised}_{t=0}$	1.459***	0.134
$\hat{\lambda}$	0.120***	0.039
Sample	23 306	

Note: Using GUiNZ data and own calculations. Standard errors in parenthesis, significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Regression results (average partial effects)

	Full	By mother's ethnicity			
	sample	NZ European	Māori	Pasifika	Asian
Basic specification	0.209***	0.196***	0.246***	0.218***	0.213***
	(0.035)	(0.043)	(0.078)	(0.121)	(0.093)
Individuals	4 778	2 958	597	556	667
w/o intent to immunise	0.220***	0.210***	0.347***	-	-
	(0.076)	(0.086)	(0.128)		
Individuals	733	574	81		
Mother's age ≤ 25	0.136***	0.130**	0.143*	-0.004	0.064
	(0.440)	(0.061)	(0.077)	(0.051)	(0.099)
Individuals	904	407	212	154	81

Note: Using GUiNZ data and own calculations. Standard errors in parenthesis, significance level: *** p<0.01, ** p<0.05, * p<0.1.

run ethnic-specific regressions, we find greater levels of state dependence among Māori compared to the other ethnic groups.

As Table 4 shows the intention to immunise child is strongly associated with the child being vaccinated after s/he is born. However, when we do 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 immunised when born, the average size of the state dependence hardly changes. Thus, the experience of having a child immunised genuinely elevates the future likelihood of immunising the child at the next schedule. This seems to be especially the case for mothers who identify themselves as Māori, though the sample size is much smaller.

We further explore whether a mother's age impacts state dependence in immunisation. For this, we reduce our sample to mothers who are 25 years old or younger. The bottom row of Table 5 shows that state dependence drops noticeably, and the likelihood to immunise the child at t increases by, on average, 13.6 percentage points if the child was immunised at the previous milestone compared to if not.

Discouraging information In Table 2, we presented descriptive evidence that having received antenatal discouraging information on immunising the child once s/he is born can harm the likelihood of having the child immunised at the next schedule. For this reason, we extended our basic specification by interacting the lagged dependent variable with a binary indicator which takes the value 1 if the mother received such information and 0 else. Table 6 shows the respective average

Table 6: Received discouraging information D_i before childbirth[a]

	Full sample	NZ European	Māori	Pasifika	Asian
$y_{i(t-1)} = 0$ & $D_i = 0$	*reference category*				
$y_{i(t-1)} = 0$ & $D_i = 1$	-0.099***	-0.085**	-0.104	-0.073	-0.192
	(0.035)	(0.041)	(0.085)	(0.209)	(0.232)
$y_{i(t-1)} = 1$ & $D_i = 0$	0.194***	0.180***	0.238***	0.217*	0.195**
	(0.034)	(0.042)	(0.079)	(0.121)	(0.091)
$y_{i(t-1)} = 1$ & $D_i = 1$	0.177***	0.165***	0.194**	0.219*	0.182**
	(0.034)	(0.042)	(0.080)	(0.123)	(0.089)
Individuals	4 778	2 958	597	556	667

Note: Using GUiNZ data and own calculations. Standard errors in parenthesis, significance level: *** p<0.01, ** p<0.05, * p<0.1. [a] $y_{i(t-1)}$ indicates whether the child was $(= 1)$ or was not $(= 0)$ immunised at the previous schedule. D_i indicates whether the mother $(= 1)$ received antenatal discouraging information on immunising the child or else $(= 0)$.

partial effects, both for the full sample, as well as for within each ethnic group.

Reference category is that the child has not been immunised at the previous milestone $(y_{i(t-1)} = 0)$ and that the mother has not received any discouraging information $(D_i = 0)$. If the mother has received discouraging information, the likelihood of having the child immunised at t drops by, on average, 9.9 percentage points. However, if the mother has immunised the child at $t-1$, discouraging information does not cause a further substantial impact on the likelihood to immunise the child at t. This finding is relatively stable across ethnicity.

5. Conclusion

This study examines whether having a child immunised at a prior schedule *genuinely* impacts the likelihood of vaccinating the child at the following schedule. We use birth cohort data from the Growing Up in NZ study which tracks the lives of more than 6 000 Kiwi children. Importantly, this data provided immunisation status across various schedules, including at 6 weeks, 3 months, 5 months, 15 months and 48 months.

To identify the genuine impact of having the child immunised on the likelihood of the subsequent immunisation schedule, we employ a random-effects probit model. Our identification strategy also controls for the initial conditions problem (the effect of the first decision) and unobserved heterogeneity (via individual-specific time-invariant differences).

They key finding is that of strong state dependence in child immunisation outcomes. In particular, after controlling for differences in observable and unobservable characteristics as well as the initial immunisation, we find that the likelihood to immunise a child is on average 21 percentage points higher at time t if the child was immunised at $t-1$ compared to if not. There are some 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 immunise 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 immunisation coverage for Māori, relative to NZ European over time, with a worsening situation during the COVID-19 pandemic.

References

W. Arulampalam. A note on estimated coefficients in random effects probit models. *Oxford Bulletin of Economics and Statistics*, 61(4):597–602, 1999.

W. Arulampalam and M. B. Stewart. Simplified implementation of the heckman estimator of the dynamic probit model and a comparison with alternative estimators. *Oxford bulletin of economics and statistics*, 71(5):659–681, 2009.

S. Ayllón, J. Valbuena, and A. Plum. Youth unemployment and stigmatization over the business cycle in europe. *Oxford Bulletin of Economics and Statistics*, 84(1):103–129, 2022.

M. Biewen. Measuring state dependence in individual poverty histories when there is feedback to employment status and household composition. *Journal of Applied Econometrics*, 24(7):1095–1116, 2009.

J. S. Butler and R. Moffitt. A computationally efficient quadrature procedure for the one-factor multinomial probit model. *Econometrica: Journal of the Econometric Society*, pages 761–764, 1982.

N. Z. C. D. Centre. Immunisation coverage in new zealand: results of the regional immunisation coverage surveys. *Commun Dis NZ*, 92(suppl 2), 1992.

R. T. Chen. Vaccine risks: real, perceived and unknown. *Vaccine*, 17:S41–S46, 1999.

A. E. Clark and F. Etilé. Don't give up on me baby: Spousal correlation in smoking behaviour. *Journal of health economics*, 25(5):958–978, 2006.

T. Clark, K. Dasgupta, S. Lewycka, G. Pacheco, and A. Plum. Ethnic differences in the use and experience of child healthcare services in nz: An empirical examination. 2020. URL `https://workresearch.aut.ac.nz/__data/assets/pdf_file/0010/483319/report-final-final-2Dec2020.pdf`.

F. Devicienti and A. Poggi. Poverty and social exclusion: two sides of the same coin or dynamically interrelated processes? *Applied Economics*, 43(25):3549–3571, 2011.

E. J. Gangarosa, A. M. Galazka, C. R. Wolfe, L. M. Phillips, E. Miller, R. T. Chen, and R. Gangarosa. Impact of anti-vaccine movements on pertussis control: the untold story. *The Lancet*, 351(9099):356–361, 1998.

D. A. Gust, T. W. Strine, E. Maurice, P. Smith, H. Yusuf, M. Wilkinson, M. Battaglia, R. Wright, and B. Schwartz. Underimmunization among children: effects of vaccine safety concerns on immunization status. *Pediatrics*, 114(1):e16–e22, 2004.

P. Haan and M. Myck. Dynamics of health and labor market risks. *Journal of health economics*, 28(6):1116–1125, 2009.

K. He, W. J. Mack, M. Neely, L. Lewis, and V. Anand. Parental perspectives on immunizations: Impact of the covid-19 pandemic on childhood vaccine hesitancy. *Journal of community health*, 47(1):39–52, 2022.

J. J. Heckman. Heterogeneity and state dependence. In *Studies in labor markets*, pages 91–140. University of Chicago Press, 1981.

A. Miranda. Migrant networks, migrant selection, and high school graduation in mexico. In *Research in Labor Economics*. Emerald Group Publishing Limited, 2011.

S. Rabe-Hesketh and A. Skrondal. Avoiding biased versions of wooldridge's simple solution to the initial conditions problem. *Economics Letters*, 120(2):346–349, 2013.

A. Shet, K. Carr, M. C. Danovaro-Holliday, S. V. Sodha, C. Prosperi, J. Wunderlich, C. Wonodi, H. W. Reynolds, I. Mirza, M. Gacic-Dobo, et al. Impact of the sars-cov-2 pandemic on routine immunisation services: evidence of disruption and recovery from 170 countries and territories. *The Lancet Global Health*, 10 (2):e186–e194, 2022.

A. Skrondal and S. Rabe-Hesketh. Handling initial conditions and endogenous covariates in dynamic/transition models for binary data with unobserved heterogeneity. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 63(2):211–237, 2014.

M. B. Stewart. The interrelated dynamics of unemployment and low-wage employment. *Journal of applied econometrics*, 22(3):511–531, 2007.

B. Taylor, E. Miller, C. Farrington, M.-C. Petropoulos, I. Favot-Mayaud, J. Li, and P. A. Waight. Autism and measles, mumps, and rubella vaccine: no epidemiological evidence for a causal association. *The Lancet*, 353(9169):2026–2029, 1999.

N. Turner. The challenge of improving immunization coverage: the new zealand example. *Expert review of vaccines*, 11(1):9–11, 2012.

J. M. Wooldridge. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of applied econometrics*, 20(1):39–54, 2005.