Cash, and "Drops": Boosting vaccine registrations

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Abstract

Demand (registrations), supply (availability of vaccines), and throughput (administering of vaccines) are key determinants of the progress of vaccination drives globally, including Malaysia's National COVID-19 Immunisation Programme (Program Imunisasi COVID-19 Kebangsaan, *PICK*). This paper will focus on the first determinant — demand. Specifically, were major policy "shocks" effective in influencing vaccine registrations? Between 24 February 2021 to 14 June 2021 when the PICK was in progress, several interventions were applied in select districts and states. These provided "natural experiments" to assess the effect of certain policy interventions on vaccine demand. In this paper, we assess the effect of two types of interventions on vaccine registrations in the PICK programme in a difference-in-difference (DiD) and panel event study settings — (1) a cash transfer programme for vaccine recipients, and (2) two instances of parallel opt-in "first come, first serve" queues. Finally, we rationalise these findings in a simple model of individual demand with preference shocks.

Keywords: COVID-19, vaccination drive, panel event study, difference-in-difference

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1 Introduction

Equitable and widespread access to vaccines is broadly deemed a key component of resolving the COVID-19 pandemic. The broad conversation of 'returning to the pre-pandemic normal' rests on attaining herd immunity, which Kadkhoda (2021) critiques its feasibility in the context of COVID-19 due to (1) lack of lifelong immunity, (2) variable and potentially low vaccine effectiveness, and (3) high R_0. Nevertheless, Rapaka et al. (2021) documents that the major COVID-19 vaccines that have attained approval for emergency use are indeed effective in preventing severe symptomatic infections, and deaths.

The hypothesis then follows that the policy at the macro level is about administering safe and effective vaccines as widely as possible, and as quickly as possible. In rationalising this, we hit three constraints — (1) demand (how many people want the vaccine?) (2) supply (how many vaccines are available?), and (3) throughput (how many vaccines can be administer?). Of these, supply constraints can be shifted primarily by procuring more vaccines, and securing delivery timelines; this is mostly in the policymakers' control. Throughput is similar, and can be shifted by increasing or reducing resources dedicated to administering vaccines, e.g., expanding vaccination centers and staff count. Demand, however, is largely not within the direct control of policymakers. Gostin et al. (2021) discusses the difficulties in mandating vaccination amongst adults, including backlash, reduced confidence, individual autonomy, and importantly a general lack of direct policy levers. Often, vaccination mandates entail prohibition of particular activities, such as schooling access or public spaces. Hence, the individual's behaviour still takes primacy, and policy control is less direct.

Prior to February, Malaysia had secured sufficient vaccines to cover $\geq 100\%$ of its population by the end of 2021. This resolved the long-run supply constraint. In the short-run, delivery schedules were the constraint. Throughput constraints could be adjusted by reallocating health workers across the healthcare sector, as well as to expand headcount in response to demand and short-run supply. Unsurprising, demand is the "hard" constraint. Operationally, throughput needs to adjusted such that deliveries are at least "just in time for the next delivery, and new demand", such that disruptions are minimised, as stop-start costs may be substantial. Hence, it is a response variable. The policy question then reduces to how best to ramp up demand to, one, hit a desired vaccination rate in time, and, two, minimise disruptions.

To contextualise the discussion, registration for PICK, comprising three phases, was opened to the general public on 1 March 2021, then limited to adult (aged 18 and above) residents. Over the period of the study (10 March 2021 to 14 June 2021), two phases of PICK were in force — (1) Phase 1, which was restricted to 'frontliners', primarily those in the healthcare, security, and teaching profession, and (2) Phase 2, which prioritised the elderly (aged 60

and above), the differently-abled, and comorbid individuals. Registration for Phase 1 was restricted, and conducted directly through the Ministry of Health. Registration for Phase 2 was open to the public in four ways — (1) MySejahtera, the contact tracing application, (2) a dedicated hotline, (3) the PICK website, and (4) outreach programmes. The first three modes were all reliant on the registrant making an active choice to register themselves on the PICK. The demand question is one of overcoming hesitancy, specifically tipping the expected cost of signing up and receiving the vaccine, which is unobserved, to fall below the expected benefit. We provide formal intuition for this as a model of individual demand with preference shocks.

Now, the rollout of the PICK over the study period covered three major policy interventions that were implemented at the sub-national level — (1) a MYR20 cash handout for vaccine recipients in the capital of Kelantan, Kota Bharu, (2) a "first come, first serve" parallel queue for the Oxford-AstraZeneca (AZ) vaccine in Selangor and Kuala Lumpur, and (3) a second parallel queue for the AZ vaccine in Selangor, Kuala Lumpur, Johor, Penang, and Kuching District in Sarawak. These instances provided "natural experiments" to assess the effect of various policy interventions on vaccine demand, measured by vaccine registrations in a DiD and an event study settings.

The remainder of the paper will discuss the data, methodology, empirical findings, followed by a theoretical model to provide formal intuition.

2 Data

We relied on three data sets in this study — (1) the COVID-19 cases line listing collected by the Crisis Response and Preparedness Centre (CPRC) at the Ministry of Health (MOH), (2) the COVID-19 vaccine recipient line listing collected by the COVID-19 Immunisation Task Force (CITF), and (3) the vaccine registration line listing collected by the CITF. All data sets are at the individual-level. Supplementary to this is the 2020 population estimate by the Department of Statistics Malaysia (DOSM), used to scale relevant variables to state-level population. All daily flow variables (as opposed to stock variables, such as cumulative fully vaccinated individuals per population), including daily registrations, infections, and deaths, are smoothed by taking their respective 7-day moving average.

The COVID-19 cases line listing contains an exhaustive list of confirmed COVID-19 infections, along with information on demographics (including age), location (state-level), presence of comorbidities, date of test results, date of death, and status (recovered/ dead/ active). We aggregate the data set for state-level infections indexed by test results date rather than reporting date, and deaths indexed by date of death. Both variables are scaled

to the state-level population.

The vaccine recipient line listing records the exhaustive list of COVID-19 vaccine recipients, identifying individuals who have received at least one dose, as well as both doses (hence, considered "fully vaccinated"). Additional data are included on demographics, vaccine type, age, gender, and reported presence of comorbidities. The data set also identifies differently-abled individuals. We aggregate at the state-level individuals who have received at least one dose, and both doses, indexed by the day of administration. Both variables are scaled by state-level population.

Finally, the vaccine registration line listing records all valid registrations collected through the contact tracing application (MySejahtera)'s vaccination module, the CITF website's registration page, and the CITF call centre. Registrations are considered valid if the ID provided does not correspond to a vaccinated individual in the recipient line listing. Each entry in the line listing is unique by ID. We use aggregated registrations at the district-level, which is nested in the state-level aggregation. Registrations are split further into the mode of registration, as well as registrants aged 60 and above, with comorbidities and are differently-abled.

The different level of aggregation has justification in observability by the population. In Malaysia, COVID-19 infections and deaths are reported daily, with prominent social media and traditional media coverage, at the state-level. Studying responses in individual behaviour, specifically vaccine demand, then warrants selecting variables that individuals may most likely respond to, and observe easily.

3 Methodology

Our empirical strategy is twofold — (1) a difference-in-difference (DiD) regression, and (2) a panel event study design. Both seek to identify the policy effects on vaccine registration. The former averages the effect of respective policy interventions on demand over the entire post-treatment period, while the latter provides a day-specific view.

The first approach follows a panel DiD regression with district and day fixed effects (α_i and α_t, respectively) on daily district-level and state-level data. In this set-up, under the "parallel trends" assumption, where absent of the treatment and all else equal, the trend in registrations in untreated and treated districts or states would be the same, then β is the policy effect on vaccine registrations. β_{it} is the coefficient on the interaction term between a dummy indicating a treated state/ district, i.e., recipient state/ district of the policy intervention ($\{Treated\}_{it}$), and a dummy that switches on on and after the day of the intervention ($\{PostTreatment\}_{it}$). This is, hence, the DiD term, and switches on when

a treated state is in the post-treatment period. We control for infections and deaths per population, as well as fully vaccinated individuals per population in the vector X_{it}. ϵ_{it} is the unexplained variation in daily registrations.

$$\{Registration\}_{it} = \alpha_i + \alpha_t + \beta\{Treated\}_{it} * \{PostTreatment\}_{it} + \mathbf{X_{it}}\gamma + \epsilon_{it} \quad (1)$$

The second strategy uses a panel event study approach, documented in Clarke & Schythe (2020). A fixed effects linear model with district and day fixed effects is estimated, with daily new vaccine registrations as the explained variable. Specifically, we estimate the coefficients on the lead and lag dummies ($\{lagj\}$ and $\{leadk\}$, respectively), which switch on days lagging and leading the day of the intervention. For instance, in the Kota Bharu cash transfer instance, the day of announcement, 28 May 2021, was taken as the intervention day. The $\{Lead1\}$ dummy then switches on at 29 May 2021, while the $\{Lag2\}$ dummy switches on at 26 May 2021. Under the "parallel trends" assumption, the estimated coefficients correspond to the expected shift in registration trends pre- and post-intervention over time, all else equals. The vector of control variables X_{it} enter the equation in levels, as per the panel DiD regression.

$$\{Registration\}_{it} = \alpha_i + \alpha_t + \sum_{j=2}^{J} \beta_{1j} D_{it}^{(lagj)} + \sum_{k=0}^{K} \beta_{2k} D_{it}^{(leadk)} + \mathbf{X_{it}}\gamma + \epsilon_{it} \quad (2)$$

4 Empirical Findings

We used three policy interventions at the sub-national level as "natural experiments". The impact date of the intervention is tied to the announcement, rather than the actual implementation. Firstly, a MYR20 cash transfer programme starting 30 May 2021 in the district of Kota Bharu in the state of Kelantan, announced on 28 May 2021. Secondly, a "first come, first serve" queue for the AZ vaccine in Selangor and Kuala Lumpur, announced on 28 April 2021, with registrations opened on 2 May 2021. Thirdly, a second round "first come, first serve" AZ queue for Selangor, Kuala Lumpur, Johor, Penang and the district of Kuching in Sarawak, was announced on 17 May 2021, with registrations opened on 23 May for individuals aged 60 and above, followed by 25 May for individuals aged below 60. In this section, we will examine the findings from the panel DiD and the event study regressions for the respective policy interventions.

4.1 Kota Bharu Cash Transfers

The public health and development economics literature has a rich documentation of cash transfer programmes on vaccination take-up, such as in Barham & Maluccio (2009) for Nicaragua, Kusuma et al. (2017) for a clustered-randomised trial in Indonesia, and Wakadha et al. (2013) in rural Kenya. However, prior to the COVID-19 pandemic, research, and indeed vaccination mandates or promotion policies, primarily focused on childhood vaccination. The COVID-19 vaccination programme globally, at the time of analysis, focuses on adults aged 18 and above. Nonetheless, some countries, such as the USA, as documented in Tanne (2021), have rolled out the Pfizer-BioNTech Comirnaty vaccine to adolescents aged 12 and above.

The following figures show the daily trends of new registrations in Kota Bharu, and the average of other districts in Malaysia. The two-period version, which shows the cumulative over the 12 days before and after the cash transfer programme was announced, shows a slight divergence in registration trends between Kota Bharu and other districts. The lack of an obvious divergence in trend in the daily version may be a result of changing conditions in the epidemic between Kota Bharu, the rest of Kelantan and the rest of Malaysia. This sets the motivation to a regression setting, so that the variation in registrations due to the state of the epidemic and the wider vaccination drive, as well as district- or day-specific factors, can be partial-ed out, leaving behind the effect of handouts.

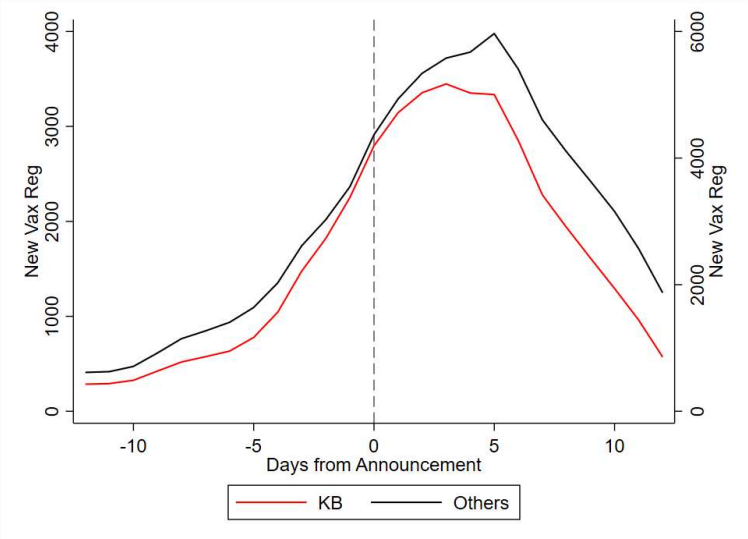

Figure 1: Average Daily Vaccine Registrations in Kota Bharu and other Districts

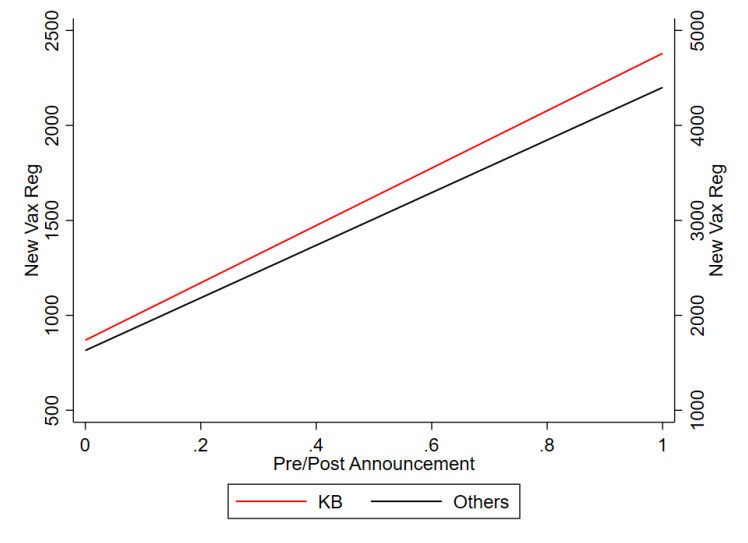

Figure 2: Daily Vaccine Registrations in Kota Bharu and other Districts: Pre- and Post-Intervention Averages

In the DiD regression with controls on infections incidence, deaths incidence, and cumulative fully vaccinated individuals as a share of the population, we find that there is a precisely estimated positive effect on registrations due to the cash handout programme. In the naïve version, without controls, the DiD term is estimated to be larger, suggesting that the broader state of the epidemic and the vaccination drive had an upward bias on the estimated policy effect. Unsurprisingly, a worse epidemic could separately induce greater urgency, while progress in the vaccination drive could create more widespread state of "fear of missing out", hence prompting more daily registrations. We further estimated the DiD regression on only the Kelantan districts. However, as deaths, infections, and vaccination rates, were included as state-level variables, they were dropped in the Kelantan-only regression.

Table 1: Panel DiD Estimates: Full Sample

VARIABLES	(1) New Registrations	(2) New Registrations
Treatment * Post-Announcement	1,116***	1,084***
	(202.6)	(189.6)
Deaths		73.99***
		(25.30)
Infections		0.888***
		(0.329)
Fully Vaccinated		-0.0256***
		(0.00723)
Constant	659.7***	1,227***
	(14.16)	(212.0)
Date FE	YES	YES
District FE	YES	YES
Observations	3,975	3,951
R-squared	0.730	0.732

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Panel DiD Estimates: Kelantan-Only

VARIABLES	(1) New Registrations
Treatment * Post-Announcement	1,234***
	(274.4)
Constant	371.2***
	(15.74)
Date FE	YES
District FE	YES
Observations	275
R-squared	0.838

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The panel event study regression frames the policy intervention with greater emphasis on the time dimension. In the lead-up to the announcement date, there was a brief uptrend in the estimated coefficients, possibly due to anticipatory effects, or leakages in the announcement timeline. Nevertheless, there was a brief increase post-announcement, although imprecisely estimated, before returning to its pre-announcement level. The cash transfer programme may have generated a brief, but noticeable, surge in registrations. Low precision in the estimates is likely due to three quirks. Firstly, the treated group is only one district. Secondly, Kelantan is a relatively small state, hence the richness of observations fell short of other larger states, such as Selangor and Kuala Lumpur.

The magnitude of impact, while noticeable, is not spectacular. A large fault may lie in the design of the policy instrument — it was largely indirect. Vaccinated individuals were requested to visit the Member of Parliament's liaison office to claim the transfer manually. This entailed additional transaction cost, offsetting part of the supposed combined benefits of receiving the vaccine, and the cash transfer. Moreover, the announcement of the programme was conducted through the Member of Parliament's office via local news outlets. An official Government announcement may have had wider reach, and the estimated effect of the programme could have been larger.

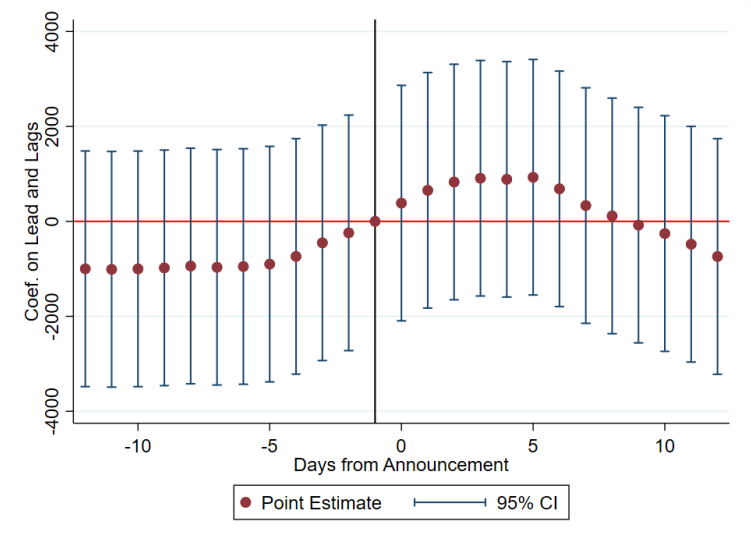

Figure 3: Event Study: Estimated Coefficients on Lead and Lag Dummies

4.2 Oxford-AstraZeneca 1.0 Opt-In

Over the period covered by this research, PICK was restricted to "frontliners", and individuals fulfilling at least one of the following criteria — (1) aged 60 and above, (2) comorbid, or (3) differently-abled. The rest of the population were not yet eligible to receive the vaccine,

even if registered. However, on 28 April 2021, the AZ vaccines received through the COVAX facility, which were taken out of PICK, were offered to all adults aged 18 and above registered on PICK, on a "first come, first serve" basis. This represented a policy shock that, firstly, created widespread publicity and attention for the vaccine programme, and secondly, created urgency given the frontloaded timeline for receiving the limited ring-fenced supply of vaccine. Registrations opened days later on 2 May 2021 for residents in Selangor and Kuala Lumpur.

Prior to the AZ 1.0 announcement, registrations in Kuala Lumpur and Selangor trended at a shallower slope than other states, but reversed course in the immediate two weeks after. In the two-period representation, we see a reversal pre- and post-announcement of the AZ 1.0 queue between the two sets of states. Controlling for the state of the epidemic and vaccination rates, the DiD term is estimated to be an imprecise positive. New deaths per population entered the model with a precisely estimated positive coefficient. A deteriorating COVID-19 situation, specifically with rising deaths, may have contributed to a surge in urgency. Indeed, the AZ 1.0 queue was announced as an "epidemic control" measure amidst rising deaths and infections in Kuala Lumpur and Selangor. As such, we may not be surprised that effect of deaths is precisely estimated but the policy effect is not.

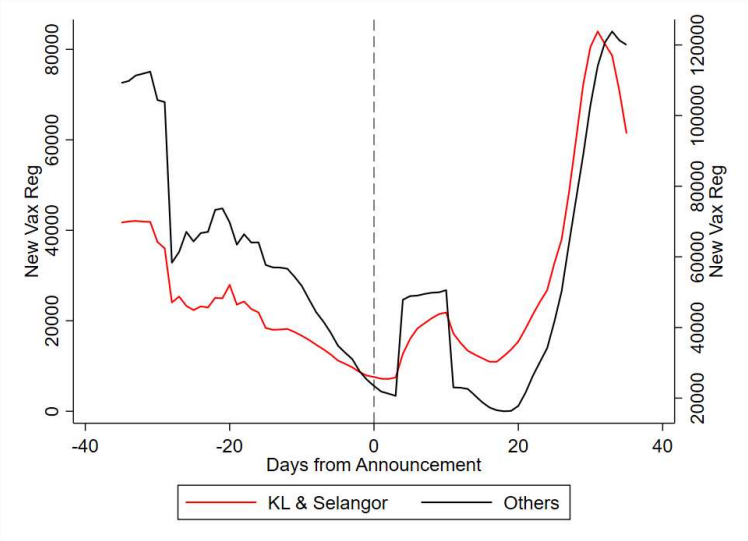

Figure 4: Average Daily Vaccine Registrations in Selangor and KL, and other States

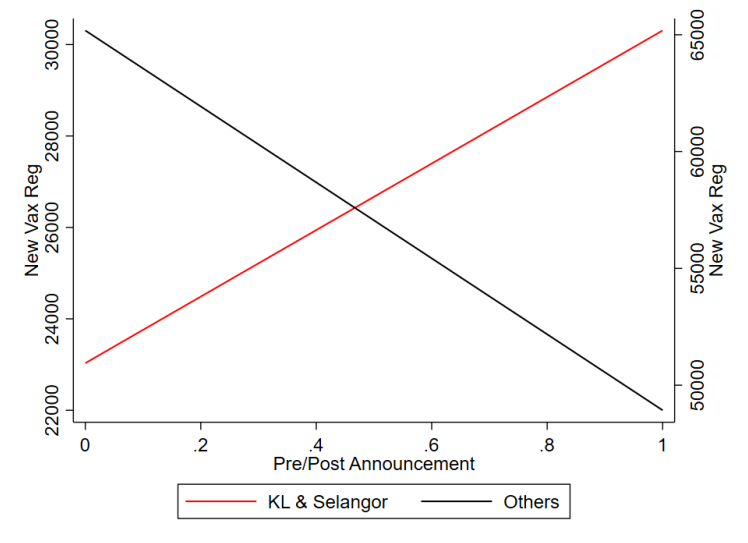

Figure 5: Daily Vaccine Registrations in Selangor and KL, and other States: Pre- and Post-Intervention Averages

Table 3: Panel DiD Estimates

VARIABLES	(1) New Registrations	(2) New Registrations
Treatment * Post-Announcement	738.0***	552.1
	(185.2)	(354.1)
Deaths		199.4**
		(90.05)
Infections		-0.278
		(0.894)
Fully Vaccinated		-0.0187
		(0.0146)
Constant	515.8***	804.7***
	(5.905)	(210.5)
Date FE	YES	YES
District FE	YES	YES
Observations	12,858	11,327
R-squared	0.691	0.697

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Whether we can discount the effects of the AZ 1.0 announcement, in and of itself, on registrations is unclear. The panel event study regression captures a large but brief surge in registrations immediately post-announcement, before returning to the around the baseline by the 20th day. Registrations were coming down prior to the AZ 1.0, either due to fears surrounding the Oxford-AstraZeneca vaccine's safety, or genuine decline in interest for the COVID-19 vaccine. In the immediate days after the announcement, registrations stayed largely unchanged. The noticeable surge corresponded to the actual launch of the sign-up form on the PICK website. New registrations, which by construction excluded those who already already registered on the PICK programme surged. While the AZ 1.0 was fully subscribed within the same day, the post-event coefficient continued to be positive and rising. Two plausible matters may be happening. Firstly, the AZ 1.0 launch generated a sense of "fear of missing out" amongst unregistered individuals, or the marginal vaccine hesitant individuals. Secondly, by observing a large number of subscription (246,000) for the vaccine, beliefs on the net benefits of signing up for, or receiving the vaccine, may have changed, pushing more unregistered individuals on the margin to sign up.

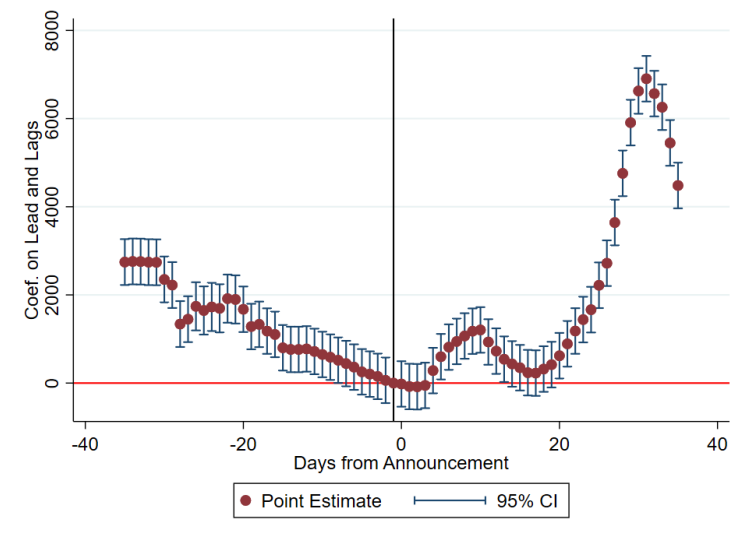

Figure 6: Event Study: Estimated Coefficients on Lead and Lag Dummies

4.3 Oxford-AstraZeneca 2.0 Opt-In

A second round of the AZ "first come, first serve" queue was announced on 17 May 2021 in two subphases. The first opened on 23 May 2021 to residents aged 60 and above, and the second on 25 May 2021 for residents aged 18 and above.

Similar to the AZ 1.0, pre-announcement trends in new registrations in the target states and districts (KL, Selangor, Johor, Penang, and the District of Kuching in Sarawak) trended

at a smaller gradient than in the rest of Malaysia. Post-announcement, the slope shifted directions. However, in the two-period version, this reversal is largely compensated, partly because of the correction by the third week post-announcement. Controlling for the state of the epidemic and vaccination rates, the effect on registrations is positive and precisely estimated. In the naïve model, the estimated effect may be upward biased. Compared to AZ 1.0 regression, the magnitude of the estimated effect is larger.

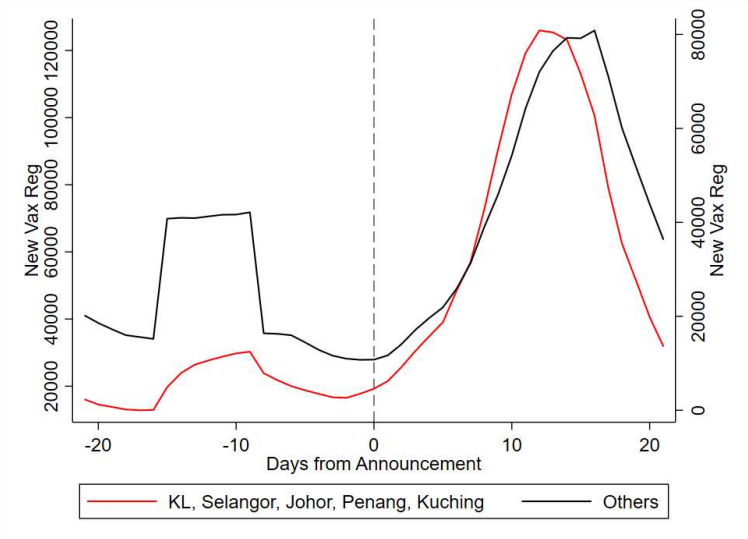

Figure 7: Average Daily Vaccine Registrations in Selangor, KL, Johor, Penang and Kuching, and other States

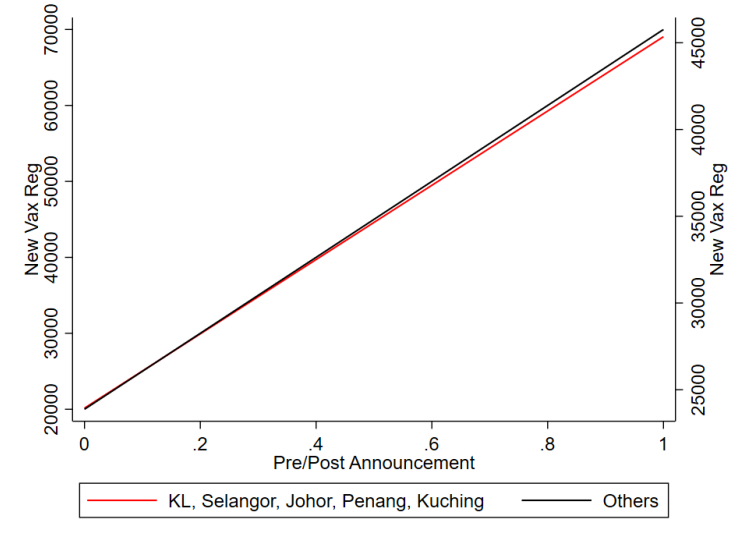

Figure 8: Daily Vaccine Registrations in Selangor, KL, Johor, Penang and Kuching, and other States: Pre- and Post-Intervention Averages

Table 4: Panel DiD Estimates

VARIABLES	(1) New Registrations	(2) New Registrations
Treatment * Post-Announcement	1,775***	1,709***
	(106.5)	(107.0)
Deaths		-6.698
		(23.43)
Infections		2.161***
		(0.332)
Fully Vaccinated		-0.0295***
		(0.00517)
Constant	364.6***	824.9***
	(9.380)	(117.7)
Date FE	YES	YES
District FE	YES	YES
Observations	6,519	6,458
R-squared	0.683	0.688

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Where the AZ 1.0 pre-announcement period was potentially confounded by hesitancy, and concerns over the safety of the AZ vaccine, these problems were likely to be less prevalent prior to AZ 2.0. However, during this time, the COVID-19 epidemic in the affected states had escalated substantially. We address this directly by controlling for deaths, infections and the vaccination rate in the panel event study regression.

In the pre-announcement period, the event time coefficients hovered close to the baseline. Precisely after the AZ 2.0 announcement, in contrast to the AZ 1.0 announcement, the event time coefficients rose substantially and are precisely estimated, but returned close to the baseline by day 20. This lack of delay may be due to AZ 1.0 having already resolved informational frictions about the AZ vaccine, and, in general, the COVID-19 vaccination drive. The key message here is less of the mode of the intervention, but that it was an informational shock in two ways. Firstly, it projected further prominence of the vaccination drive in the public sphere. Secondly, it generated discussion, and, subsequently, interest in the vaccination drive.

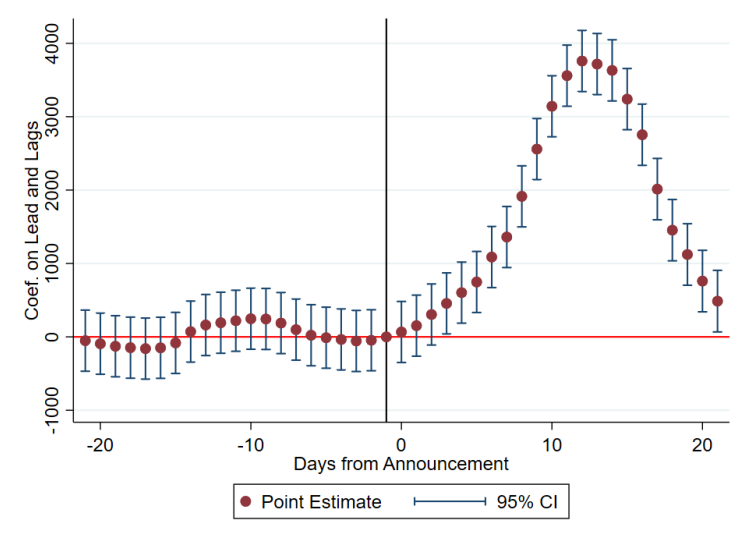

Figure 9: Event Study: Estimated Coefficients on Lead and Lag Dummies

5 Conceptual Framework

In each time period t, the daily new supply of vaccines is the sum of the domestic production of vaccines, and imports of vaccines, net of exports of vaccines. We may read each term as the daily realisation of deliveries, inbound, homebound, and outbound. Taking the expectation term gives the interpretation of scheduled inbound, homebound, and outbound deliveries.

$$V_t^S = V_t^h + V_t^m - V_t^x \tag{3}$$

The effective supply of vaccines is the cumulative supply of vaccines to date, subtract the effective demand of vaccines, i.e., vaccines that have already been administered by date t.

$$\mathbb{E}_t \bar{V}_T^S = \int_0^T \mathbb{E}_t V_t^S dt - \int_0^T \mathbb{E}_t \bar{V}_t^D dt = \int_0^T \mathbb{E}_t (V_t^{Sh} + V_t^{Sm}) dt - \int_0^T \mathbb{E}_t \bar{V}_t^D dt \tag{4}$$

Throughput at any date t is a function of two variables — (1) the effective supply of vaccines (how many vaccines do we have left?), and (2) capacity of vaccination centres (how many vaccines can we administer, irrespective of other constraints?). The smaller of which poses the binding constraint. We can think of vaccination capacity as a function of labour (L_t), and facilities (F_t).

$$\tau_t = \min\{\bar{V}_t^S, D(F_t, L_t)\} \tag{5}$$

Individual i will decide on their desired vaccination status by considering the expected utility net of the expected cost of receiving the vaccine. The individual demand is further influenced by a preference shock, ξ_{it}. This term is only known at the point of the individual i deciding their vaccine demand at time t. This shock is exogenous to the individual's preference structure. Suppose a vaccine hesitant individual, such that $\mathbb{E}(\mathcal{U}(v_{it}) - C(v_{it})) < 0$, who will not sign up vaccine. In the event of a sufficiently large positive preference shock, such that $\mathbb{E}(\mathcal{U}(v_{it}) - C(v_{it}))) + \xi_{it} > 0$, the individual i will demand the vaccine. Once demand for all individuals i in time t is set, we aggregate for the total demand in day t. As every day, individuals get vaccinated, we take them as a stock of $\hat{V}_T$ individuals up to day T. Effective demand is the total demand for vaccines, net of individuals who have already been vaccinated, hence no longer relevant in the market for vaccines.

$$V_{it}^D \equiv \max_{v_{it}} \{\mathbb{E}_t(\mathcal{U}(v_{it}) - C(v_{it})) + \xi_{it}\} \tag{6}$$

$$V_t^D = \int_0^N V_{it}^D di \tag{7}$$

$$\bar{V}_T^D = \int_0^T V_t^D dt - \hat{V}_T \tag{8}$$

Taken together, the administration of vaccines, V_t^*, in time t is the smaller of the throughput, τ_t, and effective demand, $\bar{V}_t^D$. This function mimics, in principle, the operations of vaccination drives globally, where a stock of individuals who are willing to be vaccinated form a queue, constrained by the daily capacity of vaccination centers, workers available for the vaccination drive, and stock of vaccines. In the long run, the the number of vaccines administered is constrained by the long-run supply and demand of vaccines, rather than throughput. This underpins the primacy of demand. Long-run supply can be augmented by adjusting production, exports and imports of vaccines in the economy, hence largely in control of the policymaker, but not necessarily demand, as parameters are in the control of individuals.

$$V_t^* = \min\{\tau_t, \bar{V}_t^D\} \tag{9}$$

$$V^* = \int_0^\infty \min\{V_t^S, V_t^D\} dt \tag{10}$$

In this conceptual framework, we abstract away from the need to have "just in time" ad-

ministration of vaccines, such that the daily rate of vaccination ought to be non-zero and non-negative, or above a particular threshold. Instead, we focus on the individual preference shock term. Suppose then ξ_{it} comprises two parts — a purely exogenous term (noise), ϵ_{it}, and a term that is responds to existing information circulating in the public sphere (incentive term), η_{it}. This provides scope for the policymakers to influence preferences beyond the deterministic $\mathcal{U}(v_{it})$ and $C(v_{it})$ terms, hence shaping demand for vaccines $\bar{V}_t^D$. We further breakdown the incentive term as a function of (1) information on the vaccine, I_t, and (2) additional benefits from taking the vaccine, M_t. These two subterms may interact through a set of individual-unique parameters, Θ_i, and can be multiplicative. Wood & Schulman (2021) documents a range of potential policy interventions, and primarily covers both communication strategies and monetary incentives.

$$\xi_{it} = \epsilon_{it} + \eta_{it} \tag{11}$$

$$\eta_{it} = f(I_t, M_t; \Theta_i) \tag{12}$$

Within this framework, the Kota Bharu cash transfers constitute a positive shock on M_t, equivalent to MYR20. However, it generated discussion surrounding the vaccine. For instance, questions may arise as to why monetary incentive is needed, potentially amongst vaccine hesitant communities. This contributes to a negative information shock in I_t. Alternatively, the announcement may have given more prominence to PICK, and modes of registration, or within communities to pressure each other to register for the vaccine. These conjectures constitute a positive information shock, and may amplify the additional direct benefit from taking the cash transfer and the vaccine through Θ.

The AZ 1.0 and AZ 2.0 queues bear different interpretation, as there were no direct monetary benefits involved. M_t is then likely inconsequential. However, the AZ queues generated discussion on the AZ vaccine, primarily the benefits and risks associated with the vaccines, as well as the broader discussion on using vaccines as an epidemic control measure, especially in the states affected. The primal shock is then informational, I_t, and was sufficiently large to generate new registrations, net of those who have registered for PICK prior to the AZ queue announcements. These new registrations, absent of the information shock, would have not demanded the vaccine otherwise, where expected utility fell short of the cost of getting vaccinated.

The realisation of I_t and M_t in these policy interventions, and subsequently the preference shock ξ_{it}, were large enough to tip over marginal vaccine hesitant individuals. These are individuals whose negative utility gap ($\mathbb{E}_t(\mathcal{U}(v_{it}) - C(v_{it}))$) become non-negative post-shock.

The impact of the policy intervention, λ_t, is then additional demand for vaccines generated by moving from a baseline policy shock (M_{0t} and I_{0t}), which can be zero, to the implemented policy shock (M_{1t} and I_{1t}).

$$|\mathbb{E}_t(\mathcal{U}(v_{it}) - C(v_{it}))| \leq \xi_{it}(I_t, M_t; \Theta_i) \; where \; \mathbb{E}_t(\mathcal{U}(v_{it}) - C(v_{it})) < 0 \tag{13}$$

$$\lambda_t = V_{1t}^D - V_{0t}^D = V_t^D(M_{1t}, I_{1t}) - V_t^D(M_{0t}, I_{0t}) \tag{14}$$

Hence, the short- and long-run realised vaccination rates, V_t^* and V^*, can be re-expressed functions of both the impact of policy on demand λ, and the baseline demand. By extension, it is a function of the informational and direct benefit policy variables, I_t and M_t.

$$V_t^* = \min\{\tau_t, \bar{V}_t^D + \lambda_t\} \tag{15}$$

$$V^* = \int_0^\infty \min\{V_t^S, V_t^D + \lambda_t\} dt \tag{16}$$

At its core, this framework puts formal intuition to how policymakers can approach resolving constraints on the vaccination drive by addressing demand. Specifically, unlike supply and throughput constraints, the policy instrument is indirect. Positive informational flow can be amplified, and economic benefits can be offered, to induce behavioural responses amongst "fence sitters". Policy effects, and likewise the optimal policy structure, is more indirect once we account for uncertainty in parameters, especially Θ_i, which influences (1) the interaction between informational and economic policy shocks, and (2) individual responsiveness to policy shocks.

6 Conclusion

We assessed the impact of three instances of subnational-level policy interventions aimed at Malaysia's National COVID-19 Immunisation Programme (Program Imunisasi COVID-19 Kebangsaan; PICK) between 10 March 2021 and 14 June 2021 on COVID-19 vaccine registrations in a "natural experiment" setting. The first of these is a cash transfer programme in Kota Bharu district in the state of Kelantan. The second and third are the "first come, first serve" opt-in queues for the Oxford-AstraZeneca (AZ) COVID-19 vaccine, which was offered in parallel to the PICK queue. In both instances, the AZ vaccines were offered only in select

states. The 2 May release was offered to the states of Kuala Lumpur and Selangor, while the 23 May release was offered to the states of Kuala Lumpur, Selangor, Johor, Penang, and the district of Kuching in the state of Sarawak.

We undertook two empirical strategies — (1) a panel Difference-in-Difference (DiD) regression, and (2) a panel event study regression. Specifically, we attempted to estimate the effect of the respective policy interventions, a monetary incentive, and an informational shock, on daily COVID-19 vaccine registrations. To this end, we looked to three rich data sets, which contained individual-level data on COVID-19 cases, vaccine registrations, and vaccine recipients, respectively. These data sources were aggregated at the district and state levels.

In the Kota Bharu cash transfer programme, we estimated a precise and positive treatment effect in the panel DiD model on daily registrations. In a Kelantan-only specification, we found comparable and precise effects. The event study model provides a time dimension to the estimation exercise, and reported a noticeable, but imprecise, positive effect on daily registrations. However, this boost in daily registrations due to the cash transfer programme is short-lived.

The announcement of the AZ 1.0 generated a delayed response in daily registrations, as estimated in the panel event study regression, which took form only when the queue was launched officially. Two plausible explanation squares with this finding. One, the launch generated "fear of missing out" beliefs, hence boosting registrations. Two, only by observing full subscription in less than a day (246,000), prior beliefs that held back signing up or receiving the vaccine were revised. The estimated positive effect persisted even after the AZ 1.0 queue was closed, which lasted for 3 hours. The DiD estimates were imprecise, but positive.

AZ 2.0 was a similar policy intervention, but was opened firstly to residents aged 60 and above, before expanding further to residents aged 18 and above. In contrast to AZ 1.0, the event study estimates suggest that the intervention's effect on registrations was immediate at the day of announcement, rather than only when the queue was formally launched. A plausible explanation was in AZ 1.0 having resolved adverse beliefs about the AZ vaccine specifically. The DiD estimates were larger in magnutude than in AZ 1.0, and were precisely estimated.

Moreover, this paper constructed a conceptual model of individual demand with preference shocks to characterise the problem at hand. Individuals optimise their demand for vaccines by considering the expected utility, and the expected cost, of being vaccinated. However, they are subject further to a preference shock, which has two components — exogenous, and incentives. The incentive term is modelled as a function where direct benefits, e.g., monetary, interact with the information environment through a set of individual-specific parameters.

For instance, the same set of information and monetary incentives available to two individuals can trigger different responses due to their individual-specific decision calculus. As such, this provides scope for policymakers to influence demand, though indirectly through the information environment (e.g., campaigns, "fear of missing out", and information dump), and direct benefits (e.g., cash transfers).

In the short-run, the administration of vaccines is constrained by throughput, which is a function of effective supply and vaccination capacity, and demand. In the long-run, cumulative supply and demand are the constraints. Throughput and supply are straightforward policy variables. Policymakers can adjust the schedule and scale of vaccine deliveries to influence supply, and adjust the resources employed to expand the capacity of vaccination centres to change the throughput. However, demand is supposedly deterministic. In this framework, motivated by the empirical findings that registrations were indeed responsive to the policy interventions, policymakers can deploy incentive shocks, both informational, monetary or non-monetary in nature, to reshape short- and long-run vaccine demand.

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