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Moral Hazard or Pent-up Demand? Evidence from a Quasi-experiment Concerning the Introduction of Universal Health Coverage in Four Provinces of Thailand

Panyapon Pongtipan [1]

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ABSTRACT

Historically relatively few Thai people were covered by health insurance, and most medical treatment was inaccessible or expensive. The implementation of Universal Health Coverage (UHC) since 2001 has entitled everyone to affordable treatment. It was speculated that this would result in excess healthcare consumption – a moral hazard. The current study was designed to determine whether moral hazard existed here, and if so, its magnitude. The study used panel data relating to 1,129 individuals' socioeconomic circumstances and utilization of healthcare services from 2000 to 2006 in four Thai provinces (Buriram, Chachoengsao, Lopburi and Sisaket). It compared the healthcare utilization of individuals before and after the implementation of UHC. Analysis was performed using a novel estimator, a nonlinear in Extended Two-Way Fixed Effect Difference in Differences (ETWFE DID), which was applied to individual panel data to investigate changes in individual behaviors before and after the introduction of UHC. The analysis provides evidence of a temporary 2.14% increase in outpatient utilization in previously uninsured individuals immediately following the introduction of UHC. The increase may be attributed to pent-up demand or "novelty factor". There is no evidence of sustained moral hazard.

Keywords: Moral Hazard, Universal Health Coverage, Difference-in-Differences, Extended Two-way Fixed Effects (ETWFE)

[1] Ph.D. Candidate, School of Development Economics, National Institute of Development Administration
E-mail: pongtipan@gmail.com

Background and Significance of the Research Problem

Thailand is one of a group of ambitious developing countries keen to escape the middle income trap. It has high levels of inequality as is shown by its large proportion of uninsured citizens before 2001. At that time those who had low incomes or lived in rural areas had difficult and limited access to healthcare services. The country needed to take steps in order to compete with other countries and escape the middle income trap.

Universal Health Coverage (UHC) is a solution which can allow everyone to have access to the healthcare they need without suffering financial hardship.

Prior to the introduction of UHC there were four health insurance schemes: MWS (for people below the poverty line and, from 1992, the elderly, disabled and children; funded by general taxation and covering 31.5% of the population); CSMBS (current and retired civil servants, general taxation, 8.5%); SSS (formal sector workers; general taxation and employer/employee contributions, 7.2%); and VHCS (informal sector workers and their households; general taxation and employee contributions, 20.8%) (Suraratdecha et al., 2005, Supakankunti, 2001, Tangcharoensathien et al., 2008).

These four health insurance schemes did not cover the whole population: 18.5 million people (approximately 29% of the population) remained uninsured (Limwattananon et al., 2015).

UHC, also known as the 30 Baht Program or Gold Card Plan, was implemented in 2001 and extended coverage to 18.5 million previously uninsured citizens. It also replaced previous health schemes which covered citizens in the informal sector: MWS and VHCS.

UHC was initially implemented in April 2001 in six pilot provinces, and later extended to 15 provinces (June 2001) then 75 provinces (October 2001). Bangkok was the last district to join the program (April 2002). The scheme operated alongside the two other main health insurance schemes in the formal sector, CSMBS and SSS. Each scheme served different, non-overlapping, sectors of the population, so after 2002, all citizens were covered by one of the three healthcare systems.

Individuals who were previously covered by MWS were expected to co-pay no more than 30 baht per visit (about US$ 0.70 in 2001), whereas individual treatments under the old scheme were free. However, all patients under UHC had the right to refuse to pay. This made the income from this system very low – much lower than the administration cost – so in 2006, the 30 Baht co-payment was eliminated.

Currently more than 75% of the population is covered by the UHC scheme with demonstrably improved access to healthcare services (Panpiemras et al., 2011; Suraratdecha et al., 2005). Which also reduced the financial burden on Thai people – especially the poor (NaRanong & NaRanong, 2006).

However, whilst a UHC program can directly impact people in terms of cheaper healthcare, it may encourage individuals to increase their utilization of healthcare services. Moreover, an increase in such utilization leads to higher medical expenditure which government has to bear. This problem leads to a common argument against this policy under an asymmetric information theory called a *moral hazard* problem: UHC beneficiaries have a tendency to over-consume healthcare services (*ex post* moral hazard) because the care is free to them at the point of delivery, and they are also less likely to engage in preventive behaviors (*ex ante* moral hazard).

Literature Review

In health economics, the best practise in investigating changes in behaviors, including moral hazard, is a randomized controlled trial (RCT). However, RCTs are expensive to conduct, so to date there have been only three related to health economics, two of them in the United State (the RAND Health Insurance Experiment and the Oregon Health Insurance Experiment) and one in Mexico (the Seguro Popular Experiment).

To investigate moral hazard where RCTs are not possible longitudinal data (also known as panel data) can be used to measure the effects of an intervention in a "quasi-experiment." Early investigations into moral hazard using panel data were conducted in Britain, the United States, and China. The first of these (Courbage & de Coulon, 2004) used the British Household Panel survey data from 2000 to 2001 to investigate moral hazard in healthcare consumption and found no clear evidence of moral hazard. Similar results were also obtained in the United States using a panel study of income dynamics from 1999 to 2003 (Stanciole, 2008). Results from using the China Health and National Survey were similar (Lei & Lin, 2009; Ma et al., 2016).

However, Kim et al. (2015) found that in South Korea the number of days spent in hospital and number of outpatient visits were elevated among those who were Medical Aid recipients over those of Health Insurance beneficiaries.

There have been few studies in Thailand which have investigated this moral hazard effect due to the lack and limitations of available data sources. Ghislandi et al. (2015) use cross-sectional data from the Thai Health and Welfare Survey (HWS) both before and after UHC was implemented. They used the data from 1996, 2001 and 2003 and applied difference-in-differences (DID) and propensity score matching (PMS) techniques. The findings suggested UHC does not lead to *ex ante* moral hazard since it does not increase the tendency to smoke, drink or drink-drive. However, they found that UHC increase healthcare consumption including: the number of annual check-ups, the likelihood of hospitalization, the duration of hospital stays, and the level of outpatient utilization. However, they did not emphasize that this was evidence of *ex post* moral hazard since it might have been because of prior income or financial constraints.

Iyavarakul (2018) used data from the Thailand Supplement Household Socioeconomic Survey of 2007. *Ex ante* and *ex post* moral hazard were simultaneously estimated to avoid a problem of selection bias. The results confirmed the absence of both *ex ante* and *ex post* moral hazard from the introduction of UHC.

Recently, Srimuang and Pholphirul (2022) use three cross-sectional data sets from 2015, 2017 and 2019 from HWS to investigate moral hazard in dental treatment. They found evidence of moral hazard only in terms of dental care visits such as preventive care and costly restorative dental treatment in groups of people who have generously dental benefits coverage, but no evidence of overall increased dental utilization.

Other studies use healthcare utilization variables such as outpatient, inpatient, emergency or doctor visits as dependent variables. For example, Limwattananon et al. (2015) use cross-sectional data sets from 2001, 2003 and 2005 from HWS. They found evidence of increasing inpatient admission and ambulatory care. The same data sets were also used by Gruber et al. (2014) who also found increasing healthcare utilization and reduced infant mortality rate.

None of the previous studies about moral hazard effects arising from the introduction of Universal Health Coverage in Thailand has used longitudinal or panel data which allow analysis of changes in individual behavior. This research therefore is the first empirical attempt to use longitudinal data from the Townsend Thai Project to analyze moral hazard effects of the Universal Health Coverage scheme upon individuals' healthcare.

Research Objectives

This study aims to: (1) prove whether moral hazard in healthcare exists with respect to the introduction of UHC in Thailand, and (2) examine how individuals' characteristics influenced their healthcare consumption following this change.

Scope of Research

This study used a longitudinal (panel) data set from the Townsend Thai Project which started in 1997 and ran until 2017. It covered four Thai provinces: Chachoengsao and Lopburi (semi-urban provinces in the more developed central region of Thailand), and Buriram and Sisaket (rural and less developed regions in the northeast). In each of the four provinces the survey was conducted in four randomly selected villages.

The project followed a same set of approximately 600 randomly selected households. The sampled households were interviewed monthly using questionnaires which covered many aspects including household finances, individual occupation, and individual health insurance, sickness, and healthcare consumption.

The duration of the panel allows not only analysis of changes in behavior but also control for unobservable, time-invariant characteristics of both individuals and households. Moreover, since some policy changes take time to take effect, long panel data are more reliable than using cross-sectional data from just before and after a policy implementation. In the case of policies which are particularly attractive or needed (such as UHC), immediately after policy implementation people who are in a state of need might over-consume as they now have access to services which were previously unaffordable; consumption should subsequently normalize.

Because of possible composition change, the analysis was restricted to up until February 2006 in the post-treatment period. The pre-treatment period needed to be long enough to visualize and evaluate a parallel trend assumption, but not so long that there is either significant compositional change or exogenous shock which may make it unlikely for a parallel trend to hold. Consequently, the period of study was restricted to from July 2000 to February 2006 (78 months). The criteria for how to construct and identify treatment assignment and status are available on request from The Research Institute for Policy Evaluation and Design (RIPED, University of the Thai Chamber of Commerce).

Research Methodology

The estimate of difference-in-differences using standard two-way fixed effects estimation is as follows.

$$Y_{it} = \alpha_i + \alpha_t + \tau D_{it} + X_{it}\beta + \mu_{it} \quad (1)$$

Let ATT_t denotes the average treatment effect on the treated. It is defined in term of potential outcome as:

$$ATT_t = \mathbb{E}[Y_{it}(1) - Y_{it}(0) | D_{it} = 1] \quad (2)$$

where *i* and *t* index individual and survey month respectively. Y_{it} represents the dependent (outcome) variable which, in moral hazard context, is healthcare utilization.

α_i is an individual fixed effect which captures time-invariant characteristics of an individual and α_t is a time fixed effect which captures macroeconomic shock that affects individuals equally.

D_{it} is a dummy variable equal to one if individual *i* participated in the treatment group in time period *t*, otherwise zero.

X_{it} is a vector of covariates which are independent variables. It reflects individuals' characteristics, household demographics and socioeconomic characteristics following Andersen health utilization model including (1) predisposing factors such as gender and age, (2) enabling factors such as healthcare insurance, and (3) need for healthcare services (Stanciole, 2008).

β is a vector of coefficients of covariates as above.

μ_{it} are idiosyncratic and time-varying unobservable (stochastic error term).

This equation allows τ to capture the ATT_t that is, it measures the average effects of the treatment on the group which switches from being untreated to being treated.

Identification strategies for control and treatment groups are crucial in this study since the previous literature of moral hazard effect in Thailand has used different sources of data. Treatment status was assigned to individuals who have never had any prior public health insurance and then become insured with UHC after the healthcare reform of 2001. The control status in previous studies was assigned to those who worked in the formal sector and held CSMBS and SSS coverage (Ghislandi et al., 2015; Iyavarakul, 2018).

Another significant difference from the previous literature is how we observe health insurance status. Early studies that used the Thai Health and Welfare Survey or the Socioeconomic Survey of Thailand were able to distinguish type of health insurance since this was already included in survey questionnaires (Ghislandi et al., 2015; Iyavarakul, 2018).

Townsend Thai Data does not include type of health insurance directly in the survey questionnaires and so requires another approach. This study used age, occupation, type of wage/income and benefit from the employer, along with information about who paid for treatment to identify insurance coverage.

However, people in the informal sector (a majority of treatment group) may have a pattern of seasonal jobs, resulting in changes to their healthcare insurance scheme. This may violate strong exogeneity assumptions which requires the composition of the group to remain stable throughout the analysis period. In the first stage of analysis, I will assume that the treatment status is stable (absorbing treatment), once individuals receive a treatment, they cannot leave the treatment in any future periods *t*. In reality, even though individuals may change their job from formal to informal sectors, some kinds of insurance protection such as SSS extend insurance cover for a period after quitting formal employment. Informal employment is contribution-free, whilst formal employment requires a small contribution which is directly taken from wages. I argue that under such circumstances individuals are unlikely to change their behaviors with respect to healthcare utilization: it's only the convenience in visiting the healthcare provider that may change.

The introduction of UHC in Thailand started at different times (staggered adoption) according to province. Sisaket was a province in the second five pilot provinces which started in June 2001. UHC was then extended nationwide in January 2002. Table 1 shows how individuals were classified into treatment and control groups.

Table 1 Identification Criteria

Group	Sub-group	Criteria
Treatment	Early	Who never had any kind of insurance and lived in Sisaket.
	Late	Who never had any kind of insurance and lived in other provinces.
Control		Who constantly held CSMBS and SSS
Excluded		Who held MWS and VHCS and transferred to UHC

Source: Author's Study

Table 2 Description of Variables Used in This Study.

	Variables	**Meaning**
Dependent Variable	Number of outpatient utilizations	Count variable indicates number of outpatient utilizations respondents used in the previous month.
Independent Variables	Male	Dummy variable = 1 if the respondent is male, otherwise 0.
	Age	Age in years of respondents
	Married	Dummy variable = 1 if the respondent is married, otherwise 0.
	Primary	Dummy variable = 1 if the respondent has at least primary education, otherwise 0.
	Years of education	Year of education of respondents.
	Household size	Number of members in respondent's household.
	Household income	Monthly household income (median) in thousand Baht.
	Household wealth index	Household wealth index of respondent's family, calculated by ranking all households in the survey by household wealth and then partitioning them into four groups - from the poorest (group 1) to the richest (group 4).

Note: The independent variables from this table will be used to assert propensity score matching and overlapping (common support) before further analysis.

Source: Author's Study

Table 3 Descriptive Statistics of Treatment and Control Groups before Policy Intervention

	Treatment group	**Control group**	**Difference (p-value)**
Outpatient utilization	0.009	0.040	-0.031***
	(0.002)	(.009)	
Male	0.520	0.520	0.000
	(0.017)	(0.030)	
Age	36.560	35.996	0.563
	(0.406)	(1.085)	
Married	0.699	0.608	0.091***
	(0.016)	(0.030)	
Primary Education	0.223	0.418	-0.194***
	(0.014)	(0.030)	
Years of education	5.494	7.128	-1.631***
	(0.098)	(0.287)	
Household size	4.923	5.139	-0.216
	(0.074)	(0.136)	
Household income	20.363	29.949	-9.585***
	(2.894)	(3.162)	
Household wealth index	2.435	2.982	-0.547***
	(0.038)	(0.064)	
No. of individuals	856	273	
No. of observations	12,923	4,673	

Note: Standard deviations in parentheses. Summary statistics for individual characteristics calculated based on 18 months prior to policy reform. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels using t-test.

Source: Author's Calculation

After classifying individuals into treatment and control groups, the baseline characteristics from Table 2 will be used to calculate propensity score to find the overlapping (common support) between these two groups. This process is to assure that the groups are comparable and to reduce extrapolating outside individuals' shared characteristics. It can be seen in Table 3 that some of individual characteristics such as marital status, level of education, household income and household wealth differ significantly between treatment and control groups. Figure 1 shows the process of analysis.

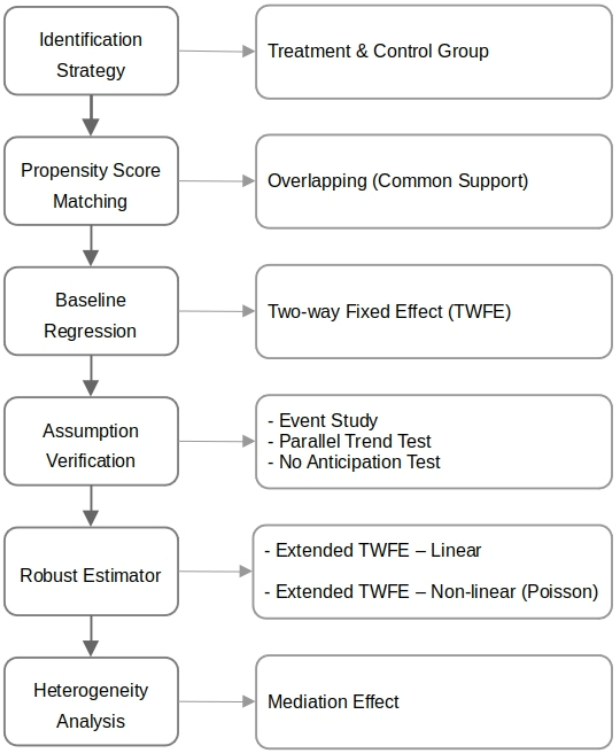

Figure 1 Methodology Framework and Process of Analysis
Source: Author's Study

Conventional estimation methods using standard two-way fixed effect in difference-in-differences research design in the context of staggered adoption have been widely discussed recently. Concerns have been raised by economists and econometricians due to potential problems arising from the weight of heterogeneous treatment effects across individuals and time. The weight problem is caused by comparison between treated groups with already treated groups as control (Goodman-Bacon, 2021; de Chaisemartin & D'Haultfoeuille, 2020; Callaway & Sant'Anna, 2021; Sun & Abraham, 2021).

To correct for this problem, Wooldridge (2021, 2023) proposed a new method termed Extended Two-way Fixed Effect (ETWFE) which allows for sufficiency heterogeneous treatment effects over time and across groups, yielding a robust estimator. The new method also can be applied to non-linear settings when outcome of interest is in count, binary or fractional form. Moreover, the ETWFE method also has a degree of resilience to the case that the data are unbalanced and utilizes more of the data than previous methods.

Another benefit of this new method is that it can be modified to verify the parallel trend assumption and also correct for it when the assumption does not hold. It can also be modified to verify no-anticipation assumptions and attrition bias in the case of unbalanced panel data.

For outcomes such as count data, which are nonnegative integers without a natural upper bound, the model **G(.)** in equation 3 will employ the exponential mean function coupled with Poisson quasi-log likelihood (QLL) in pooled quasi-maximum likelihood (QML) estimation.

For individual *i*, *g* indicates a group of individuals and *t* indicates calendar time. The first-time treatment occurs at time $t = q$. In this analysis I defined a vector of group indicators, *D*, identified by when an individual is exposed to treatment for the first time. Once individuals get exposed to treatment, they remain treated though out the period of analysis. For the purpose of the model the control group, never treated group, are assumed to have been treated in period infinity, $t = \infty$.

$$Y_{it} = G\left[\alpha + \sum_{g=q}^{T}\beta_g D_{ig} + X_i\kappa + \sum_{g=q}^{T}(D_{ig}.X_i)\eta_g + \sum_{s=2}^{T}\gamma_s f_{st} + \sum_{s=2}^{T}(fs_t.X_i)\pi_i + \sum_{g=q}^{T}\sum_{s=g}^{T}\delta_{gs}(W_{it}.D_{ig}.fs_t) + \sum_{g=q}^{T}\sum_{s=g}^{T}(W_{it}.D_{ig}.fs_t.\dot{X}_{ig})\xi_{gs} + \underbrace{\sum_{g=q}^{T}\Omega_g(D_{ig}t)}_{\text{cohort-specific trend}}\right] + \mu_{it} \quad (3)$$

$\mathbf{X_i}$ is a vector of time-invariant pre-treatment including strict exogeneity time-varying covariates: gender, education, age. The individual's age represents an example of a strict exogeneity time-varying covariate in this model.

$\mathbf{f_{st}}$ is a set of mutually exclusive time dummies which can have only two values, all zero for control group, one for treated group *g* after first exposed to treatment at *t=q*, otherwise zero (pre-treatment period).

$\dot{\mathbf{X}}_{\mathbf{ig}}$ is the cohort-specific means of covariates. A cohort is defined as a group consisting of all individuals who were first treated at the same time.

$$\dot{X}_{ig} \equiv X_i - \mathbb{E}(X_i|D_{ig} = 1) = X_i - \overline{X}_g = X_i - N_g^{-1}\sum_{h=1}^{N} D_{hi}X_h \quad (4)$$

δ_{gs} can be interpreted as the ATT which also resulted from centering covariates so making δ_{gs} easier to interpret.

ξ_{gs} represents heterogeneous treatment effects which are also known as "moderating effects". These coefficients allow capture of how treatment effects vary between various sup-populations.

The ATTs can be aggregated by group and time to generate a cohort specific aggregate treatment effect. Similarly, they can be aggregated for an overall treatment effect. They can also be aggregated to form calendar and event effects.

In case of violation of the parallel trends assumption, the equation will be extended by including cohort-specific time trends for both linear and non-linear G(.) specifications.

To verify the parallel trend assumption, perform the following joint test:

$$H_0 : \Omega_g = 0 \text{ for } g = q, .., T$$
$$H_0 : \Omega_{June'01} = \Omega_{Jan'02} = 0 \quad (5)$$

In this analysis, *q* is referred to as a cohort-specific group. For example, Sisaket was the only province which implement UHC in June 2001. The other three provinces later implemented it in January 2002.

If the results show that the null hypothesis was rejected, it means that there has been a violation of the parallel trend assumption. However, including cohort-specific time trends will help address the problem as they act as to correct the violation of the parallel trend assumption. In the case in which null hypothesis of parallel trends is not rejected, it is not advisable to include cohort-specific linear or non-linear trends since doing so will introduce further unnecessary multicollinearity in the model.

Results

The main research design used in this analysis is DID. It's first assumption states that in the absence of treatment, both groups will have a similar evolution of outcome.

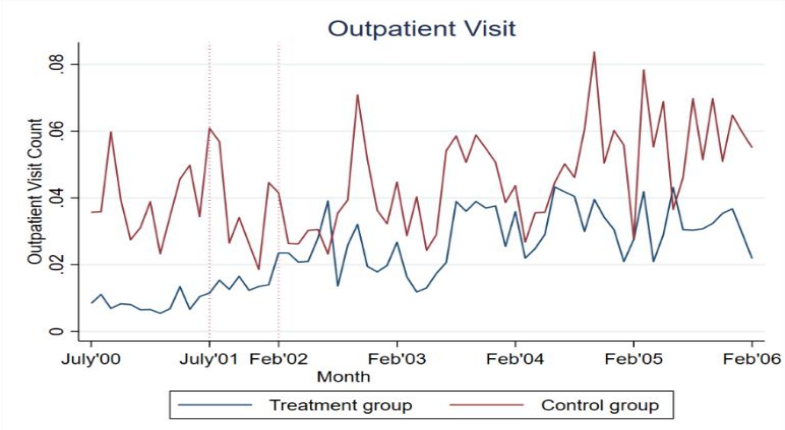

Figure 2 Mean outpatient utilization before and after UHC implementation. The vertical dashed lines represent the months of UHC implementation

Source: Author's Calculation

Figure 2 shows average outpatient healthcare utilization in the treatment and control groups. The trends of outpatient utilization were rising in both treatment and control groups prior to July 2001. It is clear how outpatient utilization increased in the treatment group immediately after July 2001, but declined in the control group. However, after mid-2002 both the treatment and control group trends move together, as they did before July 2001. This visualization suggests that the parallel trend assumption holds. The event study and the joint test results will subsequently confirm the validity of the parallel trend assumption.

Event Study Results

Consider the event study which is referred to as a dynamic difference-in-differences: this specification allows for time-varying treatment effects and shows the long-term effects of an intervention. The main purposes are to visualize the parallel trends assumption and observed the treatment effect heterogeneity over time.

$$Y_{i,t} = \alpha_i + \lambda_t + \underbrace{\sum_{\ell=-K}^{-2} \beta_\ell D_{i,g,t}^{\ell}}_{\text{leads}} + \underbrace{\sum_{\ell=0}^{L} \beta_\ell D_{i,g,t}^{\ell}}_{\text{lags}} + X_{i,g,t}'\Gamma + \nu_{i,t} \quad (6)$$

Individuals in the treatment group consume or utilize healthcare services β_ℓ more than individuals in control group ℓ months after treatment relative to the difference in the months before treatment.

β_ℓ can be interpreted as the effect of treatment for different lengths of exposure to the treatment. In the event study frameworks $\beta_{\ell-1}$ is normalized to be equal to zero in the reference period. This also resolves the multicollinearity problem. The estimation of β_0 (beta zero) is an instantaneous (or contemporaneous) treatment effect and refers to the average treatment effect in the first period after the policy is implemented. Note that, in causal inference, the positive values of ℓ represent treatment lags. This is the opposite of the lag sense in general understanding or financial economics. The estimate of β_ℓ is, in effect, the coefficient on the ℓ^{th} lag. Generally speaking, this is the average effect of treatment ℓ periods after the first (immediate) adoption period.

Recently Sun and Abraham (2021) found that in the setting of staggered adoption the coefficient is contaminated by the effects from other periods, so the coefficients do not necessarily capture the true dynamic treatment effects. To identify those true coefficients with differential timing adoption, Sun and Abraham (2021) recommend dropping two leads term, not just first the lead term. To circumvent this issue, I modified the original package "eventstudyinteract" (Sun & Abraham, 2021) to accommodate the count data in the Poisson model.

Figure 3 shows dynamic treatment effect estimates for the effect of the introduction UHC using equation 6. Estimates before the introduction of UHC are close to zero and are never statistically significant at the 5% level. This provides evidence to favor the parallel trend assumption. Estimates start increasing and are statistically significant at the 5% level after the introduction of UHC. After peaking at five months, the estimates start to decline, becoming statistically insignificant towards the end of the analysis period.

Figure 3 also shows, as expected, no anticipatory effect in the time prior to introduction of UHC which differs from other policy introductions, for example cash transfer or minimum wages; those policies induce people to behave differently before the policy actually starts.

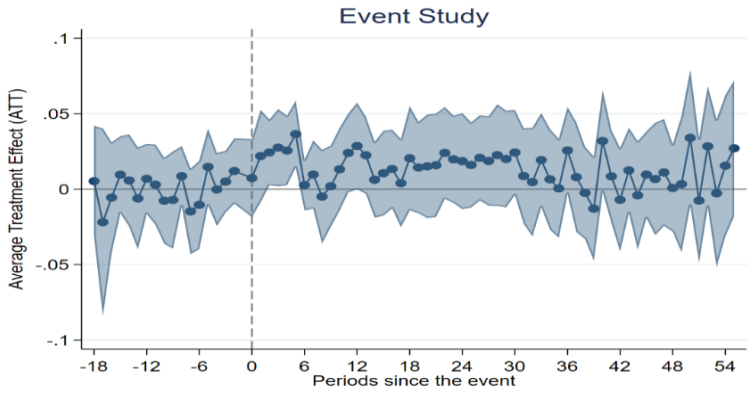

Figure 3 Dynamic Treatment Effect

Note: This figure plots ATT (and 95 percent confidence intervals) from estimation based on the modified eventstudyinteract package.

Source: Author's Calculation

Extended Two-way Fixed Effect Results

Table 4 shows the results for both the simple model when **G(.)** is a linear function estimate using ordinary least squares (first column) in equation 3 then follow with a more complicated one where **G(.)** is a non-linear exhibits exponential mean function coupled with the Poisson QLL in pooled QML estimation (second column).

Estimates of the effect of introducing UHC are positive and show little difference in aggregated average treatment effect between these two models. However, according to the Poisson model, which is correctly specified to accommodate the behavior of count data in health econometric space that is often highly skewed with mass zeros, overall the individuals in the treatment group who were previously uninsured experienced a 2.14% significant increase in outpatient utilization following the introduction of UHC in July 2001.

The results also show that the treatment effects are both positive and significant for the early and late treatment groups. However, the treatment effect in the early treatment group (individuals who were previously uninsured in Sisaket) is higher than for the late treatment group (individuals who were previously uninsured in the other three provinces). This can be explained as the effect of the focused government information campaign which included Sisaket in the group of pilot provinces before nationwide UHC implementation.

The ETWFE also provides the moderating effect, which in this case can refer to a Conditional Average Treatment Effect on treated (CATE). This is one of the benefits of using ETWFE, since the covariates used in DID need to be time-invariant or at least strictly exogenous. Traditional TWFE will not be able to recover CATE because the estimation process will drop those time-invariant covariates.

According to the estimations of the moderating effects, previously uninsured individuals who are older are more likely to consume more healthcare. In contrast, those who are better educated are likely to consume less healthcare. Finally, there is no differences in healthcare utilization between the genders.

Table 4 Result from Using Extended Two-way Fixed Effect Model

	Ordinary Least Squares (Linear)	**Poisson (Non-linear)**
Aggregated ATT	0.0167***	0.0214***
	(0.0003)	(0.0009)
Early treated ATT	0.0186***	0.0256***
	(0.0001)	(0.0018)
Late treated ATT	0.0145***	0.0166***
	(0.0001)	(0.0002)
Male	-0.0194	-0.8362
	(0.0162)	(0.6690)
Age	0.0014***	0.0256*
	(0.0006)	(0.0137)
Education	-0.0042***	-0.1299*
	(0.0015)	(0.0676)
Number of individuals	1123	1123
Number of observations	63424	63424
R^2	0.0307	-
BIC	-	29879.6

Table 4 (Continued)

Note: Robust clustered standard errors by individual shown in parentheses. The standard errors were estimated using the delta method. p-value and 95% confidence intervals for aggregate ATTs calculated from bootstrapping. BIC: Bayesian Information Criterion. *** $p < 0.01$; **$p < 0.05$; *$p < 0.1$.

To provide more concrete evidence of no violation of parallel trend assumptions, rather than relying on visualized the trend graph in figure 2 and event study in figure 3, I also re-estimated the model with cohort specific in both linear and exponential time trends, as depicted in equation 3. The results are shown in Table 5. The overall joint test results do not reject the null hypothesis of parallel trend in both linear and exponential time trends.

Table 5 Joint Test for Violation of Parallel Trends Assumption

	Linear trends	**Exponential trend**
Early treated group	0.0004	-0.0589
	(0.0005)	(0.0996)
Late treated group	0.0004	0.0152
	(0.0006)	(0.0235)
Joint test result	Chi2(2) = 0.24	Chi2(2) = 0.83
	Prob>chi2 = 0.7858	Prob>chi2 = 0.6590

Note: None of the above results was significant at $p < 0.1$ level.

Source: Author's Study

Discussion and Conclusion

It has been suggested that when beneficiaries share a portion of the cost burden, they will be more prudent with their healthcare visits and reduce the overall cost of healthcare. However, healthcare does not follow the normal goods assumption that price reduction leads to more consumption since, in general, people do not enjoy visiting to see a doctor – even if it is free. Indeed, visiting a healthcare provider still costs the patients, both monetarily (e.g. transportation costs), and non-monetarily, in the form of opportunity costs such as forgone income by missing work (Lucifora & Vigani, 2018). Patients also bear the utility loss from waiting, potentially for many hours and surrounded by sick people, before seeing a doctor.

In this study, I evaluated the intervention of UHC by using long survey panel data with extended research designs. Using these data with the novel estimations, I found a slight overuse

in healthcare utilization in the treatment group relative to the control group following the introduction of UHC. The magnitude of this overuse gradually declined over time. Ghislandi et al., (2015) found a similar post-treatment increase, but their study, being short term, did not identify a subsequent normalization in healthcare utilization.

This overuse and subsequent normalization can be explained in two ways: (1) prior to the introduction of UHC, there was a "backlog" of untreated condition leading to elevated treatment demand once UHC was introduced, i.e. pent-up demand; (2) given the lack of experience of medical treatment prior introduction of UHC, engaging with health services could be seen as novel and interesting leading to an initial surge in demand for treatment out of curiosity. The normalization of demand overtime may be attributed to: (1) the elimination of the "backlog" through treatment and/or (2) a fading of the novelty factor. In summary, this study provides no evidence of a sustained moral hazard.

Suggestions

Application

As other researchers have indicated, zero or low-cost healthcare insurance may lead to unwanted behaviors and there is a trade-off between the welfare gains and moral hazard. Increased healthcare utilization by the previously uninsured would mean that the policy is really working: better access to healthcare through UHC not only leads to improved individual health but may also lead to improved health education benefiting not only individuals but also their families. This may lead to improved overall health behaviors and outcomes, possibly helping to offset the cost.

The benefits of improved health following the introduction of UHC are not limited to individuals and their families, but also extend to the workplaces, to the economy, and to society in general.

Given the importance of understanding the relationship between individuals' behaviors and the availability and affordability of healthcare, there is a need for panel data covering individuals' socioeconomics, insurance coverage and behaviors (both healthy and unhealthy).

Given the negligible moral hazard following the introduction of UHC and the clear benefit to the health of individuals, UHC should be extended to cover additional group within Thailand's boundaries including non-citizen groups such as unregistered hill tribes people and refugees.

Further Research

For further study, the Townsend data source also contains details about diseases and symptoms. Researchers in the medical area might therefore find it beneficial for in-depth analyses of patient responses and behaviors.

Such rich data also open up for researchers opportunities to apply more complicated, and possibly more suited, approaches to analysis; DID research design relies heavily upon many strong assumptions, and recently developments in this area have tried to relax those assumptions, for example, in case of treatment that can be switched on and off (de Chaisemartin and D'Haultfœuille , 2023), or in case of continuous treatment (Callaway et al., 2021), and with recent developments in machine learning such as causal forest there may be opportunities to provide deeper insights into the data.

Using other datasets available in Thailand such as The Household Socio-Economic Survey and Health and Welfare Survey from National Statistical Office of Thailand (both of which are cross-sectional) researchers may be able to apply propensity score matching to create pseudo-panel datasets. Such an approach may yield similar results to this research. However, with recent changes in benefits for each insurance type such as the expansion of UHC benefit coverage and the contraction in CSMBS coverage the results may show moral hazard in individuals covered by UHC, a scheme which has more generous benefits than both CSMBS and SSS.

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