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# **The Demand for A COVID-19 Vaccine**

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## **[Abstract]**

Taking willingness to pay as primitive, this paper establishes an analytical framework for demand estimation, where the estimator is robust to endogeneity of price. Applying the framework, this paper then estimates demand functions for a COVID-19 vaccine and compute the consumer surplus in both China and the UAE. We find that the price elasticities of demand are mostly greater than one in both countries. An elastic demand suggests subsidy is likely to be successful in promoting vaccination. The consumer surplus is sizeable, around 58 billion US\$ in China and 646 million US\$ in the UAE. The figures can inform policymakers in assessing their vaccine programs.

## **[Key Words]**

Demand for vaccine, Demand estimation, Willingness to pay, COVID-19, Contingent valuation, China, UAE

## **[JEL Classification]**

D12, I12

**Declarations of interest:** none

## 1. Introduction

The pandemic of the coronavirus disease 2019 (COVID-19) has created a significantly negative impact on different aspects of human life worldwide. As such, researchers have endeavoured to tackle COVID-19 and the virus (SARS-CoV-2) that causes the disease, for example by developing vaccines (see among others Graham, 2020; Le et al., 2020).

With the development of COVID-19 vaccines, a number of studies explored consumers' willingness to pay (WTP) for the COVID-19 vaccine in different countries (see Cerda and García, 2021; Dias-Godói et al., 2021; García and Cerda, 2020; Harapan et al., 2020; Muqattash et al., 2020; Qin et al., 2021; Sarasty et al., 2020; Vo et al., 2021; Wang et al., 2021; Wong et al., 2020). As will be discussed in Section 2, these studies generally found that different consumers have different WTP, which in turn depends on a number of factors, such as income. Nevertheless, this strand of research did not estimate a demand function for a COVID-19 vaccine explicitly.

Filling this gap, this study takes one step further to estimate demand functions for a COVID-19 vaccine in China and the United Arab Emirates (UAE) and compute the associated consumer surplus, utilizing the WTP data made available by Qin et al. (2021) and Muqattash et al. (2020). For this purpose, we first establish an analytical framework, under three weak behavioural assumptions which can be relaxed if one wishes. In our analytical framework, the proposed estimator is robust to the endogeneity of price, an issue that has plagued demand estimations with observational data, in that by construction the right-hand-side variables (including price) is asymptotically orthogonal to the error term in the estimation. Armed with the analytical framework, we then proceed to estimate the demand functions and compute the consumer surplus in China and UAE. Understanding the demand for a COVID-19 vaccine and the associated consumer surplus is meaningful as the knowledge can help policymakers to fine-tune and assess their vaccine programs and vaccine producers to better set their prices in the future.

Our estimations find that the price elasticities of demand for a COVID-19 vaccine are mostly larger than one in both countries. With an elastic demand, subsidy is likely to be effective in promoting vaccination. As for consumer surplus, we find that it is as large as around 58 billion US\$ (400 billion Chinese yuan) in China and 646 million US\$ (2,374 million AED) in the UAE. Policymakers can utilize the estimates of consumer surplus in the assessment of their vaccine programs.

The contribution of this study is two folds. First, we contribute to existing studies that investigated consumers' WTP for a COVID-19 vaccine by an in-depth analysis of the demand function. The finding from this study can inform policymakers in assessing their vaccine programs. Second, we propose an analytical framework that can be utilized to estimate a demand function elsewhere, particularly for goods that do not have an actual market. With WTP data in hand, our analytical framework is easy to implement and is immune to the endogeneity of price. In addition, the Law of Demand is guaranteed to satisfy.

The rest of the paper is organized into five sections. Section 2 briefly surveys existing studies, and identifies the gap. Section 3 establishes the analytical framework, where we

develop the estimator. Section 4 presents the data, and in Section 5, we report the estimation and compute the consumer surplus. Section 6 concludes the study.

## 2. Related Literature

This study intends to estimate demands for the COVID-19 vaccine and compute the associated consumer surplus, taking consumers' WTP data as the input. Therefore, it is specifically related to two strands of research, namely those that solicit consumers' WTP for a COVID-19 vaccine and those that estimate a demand function for a particular commodity.

A number of studies are dedicated to elicit consumers' WTP for a COVID-19 vaccine in different countries. In Brazil, Dias-Godói et al. (2021) conducted a cross-sectional study on the WTP for a hypothetical COVID-19 vaccine (with a 50% efficacy) with consumers from five regions of Brazil. They interviewed 1,402 individuals who aged 18 and above and declared not to have COVID-19 at the time of interview. They found an acceptability for the hypothetical vaccine of 80.7%, and Brazilian consumers are willing to pay US\$ 22.18 for the hypothetical vaccine.

In Chile, García and Cerda (2020) utilized the contingent valuation method (CVM) to estimate Chilean consumers' WTP for a hypothetical COVID-19 vaccine, and explored factors that affect WTP. Their study covered 566 individuals, and found a WTP of US\$ 184.72, implying a social valuation of around US\$ 2,232 million. In addition, they found WTP depends on the pre-existence of chronic disease, knowledge of COVID-19, being sick with COVID-19, perception of government performance, employment status, income, health care, adaptation to quarantine with children at home, and whether the person has recovered from COVID-19. Similarly, Cerda and García (2021) explored Chilean consumers' WTP for a COVID-19 vaccine by utilizing the CVM with 531 individuals who are mainly from the middle and high-income socioeconomic groups between 10 July and 10 August 2020. They found a high WTP, with a value up to US\$ 232.

In China, Qin et al. (2021) surveyed 1,188 randomly selected respondents in China from 11 to 13 March 2020 to investigate Chinese consumers' WTP for a COVID-19 vaccine. They found around 79% of respondents were willing to get vaccinated, and the average WTP for a COVID-19 vaccine shot is 130.45 yuan (US\$ 18.9). In particular, the elderly people have a lower WTP. They released their data in the publisher's website, which we will use in this study. Similarly, Wang et al. (2021) utilized a network stratified random sampling survey from 1 to 18 March 2020 in China to explore consumers' WTP for a COVID-19 vaccine. Their study covered 2,058 respondents and estimated an average WTP of 254 yuan (US\$ 36.8), with a median of 100 yuan (US\$ 14.5).

Sarasty et al. (2020) investigated the WTP for a COVID-19 vaccine in Ecuador, using an online survey conducted from 2 to 7 April 2020 which covered a sample size of 1,050. They used the CVM to elicit WTP, and found that more than 85% of respondents were willing to pay a positive amount for the COVID-19 vaccine, and the average WTP ranged from US\$ 147.61 to 196.65, with the median from US\$ 76.9 to 102.5. In addition, income, employment status, the perceived probability of needing hospitalization if contracting the virus, and region of residence affect the WTP.

Harapan et al. (2020) studied Indonesian consumers' WTP for a COVID-19 vaccine. The CVM with an online survey was used to solicit WTP, which was regressed against a set of factors to assess its determinants. Out of the 1,459 responses, around 78% were willing to pay for a COVID-19 vaccine, with a mean and median of US\$ 57.20 and US\$ 30.94 respectively. They found that health-care workers, high income people and people with a high perceived risk tend to have higher WTP.

In a cross-sectional survey from 3 to 12 April 2020 in Malaysia, Wong et al. (2020) utilized the health belief model to evaluate the predictors of the intent of vaccination and the WTP. They solicited respondents' WTP by using a one-item question ("*What is the maximum amount you are willing to pay for the COVID-19 vaccine per dose?*") with a six-point scale. With a total of 1,159 complete responses, they found the mean and standard deviation of WTP for a COVID-19 vaccine shot to be MYR\$ 134.0 (US\$ 30.66) and MYR\$ 79.2 (US\$ 18.12).

Vo et al. (2021) assessed Vietnamese consumers' WTP for a COVID-19 vaccine, with the CVM and a community-based survey in southern Vietnam for two weeks in May 2020. They discovered an average WTP of US\$ 85.92, with a standard deviation of US\$ 69.01. They also found WTP depends on gender, living area, monthly income, and the level of perceived risk of contracting COVID-19. Muqattash et al. (2020) conducted an online survey from 4 July to 4 Aug 2020 to collect data on stated preferences for a prospective COVID-19 vaccine, including WTP, in the UAE, which covered 1,109 participants. They made the dataset publicly available, which will be used in this study.

This study will take the WTP data as an input, and explicitly estimate demand functions for a COVID-19 vaccine in both China and UAE. As such, it differentiates itself from the above-surveyed studies, which generally utilizes the CVM in surveys to solicit consumers' WTP for a COVID-19 vaccine and explore the determinants of WTP. In contrast, we take one step further to explicitly estimate the demand function, utilizing an analytical framework that will be discussed in Section 3. As we intend to estimate a demand function, this study is related to the strand of studies on demand estimation.

The demand function has been playing an important role in economics and other fields such as marketing, and researchers have tried to estimate demand functions empirically. Frequently, estimation of a demand function starts with a particular functional form, and then researchers collect observational data to estimate the parameters of the demand function. Commonly used functional forms include the Cobb-Douglas (logarithmic linear) demand function, the constant elasticity of substitution (CES) demand function, the generalized Leontief function (Diewert, 1973), the translog functional form (Christensen et al., 1975), the almost ideal demand system (AIDS) (Deaton and Muellbauer, 1980), the minflex Laurent model (Barnett, 1983), the quadratic AIDS (Banks et al., 1997), the normalized quadratic reciprocal indirect utility function (Diewert and Wales, 1988), and the normalized quadratic expenditure function (Diewert and Wales, 1988). A difficulty in demand estimation with observational data is that observed data (price and quantity) are the market equilibrium outcome, and as such price is endogenous in the estimation. The supply side factors are frequently used as instruments for the price.

Researchers have also estimated demand as a choice modelling. That is, consumer behaviour is modelled as choosing a product out of a set of available options, in order to

maximize utility subject to a budget constraint, which in turn results in market share as a function of explanatory variables. For example, among others, Berry et al. (1995) provide a framework for estimating demand as choice modelling.

In addition to the parametric estimations, non-parametric techniques have been applied in demand estimation. Blundell et al. (2012) develop a kernel estimator of demand function that satisfies the Slutsky condition to estimate the gasoline demand in the US. More recently, partly due to the availability of large data sets, the fields of computer science and statistics have seen an increased interest in demand estimations, with a number of machine learning methods applied for this purpose. Bajari et al. (2015) discuss these methods, such as the support vector machines, LASSO, and random forests. They apply the methods to estimate the demand for salty snacks, using scanner panel data from grocery stores with more than 1.5 million observations.

Compared with this strand of research, we provide a novel approach for demand estimation, taking the WTP as primitive. Our analytical framework is immune to the issue of price endogeneity, and is particularly suitable for estimating demand for a product that does not have an actual market.

### 3. Analytical Framework

In order to estimate a demand function for a COVID-19 vaccine, we take the consumers' WTP as the primitive, establish an analytical demand function under three weak behavioural assumptions, and develop the estimator in this section. As discussed in Section 2, a number of existing studies have explored consumers' WTP for the COVID-19 vaccine in different countries. With availability of WTP data, it is feasible to take WTP as the starting point.

Let  $W$  represent WTP for a COVID-19 vaccine and  $Z$  denote a discrete index that captures all the other factors that affect the distribution of  $W$ , such as income and education, and  $Z \in \{1, 2, \dots, \bar{z}\}$ . Our analytical framework is built upon the following three behavioural assumptions:

A1: Consumers are required to purchase two doses of a COVID-19 vaccine if they decide to purchase;

A2: WTP ( $W$ ) is randomly distributed, with a conditional cumulative distribution function (CDF)  $F_{W|Z}(p)$ . The index  $Z$  is a discrete random variable<sup>1</sup> with a probability mass function (PMF)  $Pr(Z = z) = \pi_z, z \in \{1, 2, \dots, \bar{z}\}$ ;

A3: Consumers will purchase the vaccine if its price is lower than their WTP.

Assumption A1 is line with the fact that two doses are recommended for most COVID-19 vaccines. Assumption A2 requires WTP to be a random variable with a CDF and  $Z$  to be a discrete random variable with a PMF, which is a fairly weak assumption. Note  $F_{W|Z}(p)$  is also a function of  $Z$ . Assumption A3 imposes restriction on consumers' purchase behaviour, which seems reasonable. If not, one can relax A3 by assuming a consumer has a certain probability of purchasing the vaccine if its price is less than her WTP, where the

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<sup>1</sup> Note the upper-case  $Z$  is a random variable while the lower-case  $z$  is its realization.

probability can depend on the consumer characteristics, but not price. Such a relaxation does not change the subsequent analysis.

Let  $L$  denote the number of consumers in the market. Then, assumptions A1-A3 imply the following demand function,  $q: \mathcal{R}_+ \times \{1, 2, \dots, \bar{z}\} \rightarrow \mathcal{R}_+$ :

$$q = q(p, z) = [1 - F_{W|Z}(p)]\pi_z 2L \quad (1)$$

where  $q$  is the quantity of a COVID-19 vaccine;  $p$  is the price; and  $z$  is the discrete index. Within the  $L$  consumers, there are  $\pi_z L$  consumers who has characteristics  $Z = z$  by A2. Then by A2 and A3, there are  $[1 - F_{W|Z}(p)]\pi_z L$  consumers who will purchase the vaccine. As each consumer are required to purchase two doses (A1), the quantity of demand at  $(p, z)$  is  $[1 - F_{W|Z}(p)]\pi_z 2L$ .

If WTP is uniformly distributed, namely  $W|Z \sim U[0, \bar{w}(1 + \sum_{z=2}^{\bar{z}} \alpha_z 1(Z = z))]$  where we allow the upper bound of the support to depend on  $Z$ , the demand function, Equation (1), can be re-written as follows:

$$q = \pi_z 2L - \frac{\pi_z 2L}{\bar{w}(1 + \sum_{z=2}^{\bar{z}} \alpha_z 1(Z = z))} p \quad (2)$$

which is a linear function of price, with the intercept and slope depending on  $Z$ . If WTP is exponentially distributed, namely  $W|Z \sim EXP(\lambda_z)$  where  $\lambda_z = \lambda(1 + \sum_{z=2}^{\bar{z}} \alpha_z 1(Z = z))$ , the demand function becomes semi-logarithmic linear, as follows:

$$\ln(q) = \ln(\pi_z 2L) - \lambda_z p \quad (3)$$

Similarly, if WTP is Pareto distributed, namely  $W|Z \sim Pareto(\underline{w}, \alpha_z)$  where  $\underline{w}$  is the scale parameter and  $\alpha_z$  is the shape parameter, with  $\alpha_z = \alpha(1 + \sum_{z=2}^{\bar{z}} \alpha_z 1(Z = z))$ , Equation (1) produces a logarithmic linear demand function, as follows:

$$\ln(q) = \ln(\underline{w}^{\alpha_z} \pi_z 2L) - \alpha_z \ln(p) \quad (4)$$

Later, we will estimate all three forms of demand functions. The empirical estimation requires data of WTP ( $W$ ) and  $Z$  index, which can be obtained by using such techniques as the CVM. Let  $\{(w_i, z_i)\}_{i=1}^N$  denote the data of  $W$  and  $Z$ , where  $N$  is the number of WTP observations (namely for survey data, it is the number of persons interviewed), and  $w_Z^D \subset \{w_1, w_2, \dots, w_N\}$  be the set of distinct values of  $W$ , conditional on  $Z$ . We then implement the following estimation procedure:

Step 1: Conditional on  $Z$ , non-parametrically estimate  $F_{W|Z}(p)$  as  $\hat{F}_{W|Z}(p) = \frac{\sum_{i=1}^N 1(w_i \leq p)}{N}$  for each  $p \in w_Z^D$ ;

Step 2: Non-parametrically estimate the PMF of  $Z$  as  $Pr(Z = z) = \hat{\pi}_z = \frac{\sum_{i=1}^N 1(z_i = z)}{N}$  for  $z = 1, \dots, \bar{z}$  where, by slightly abusing notation,  $z_i$  denotes the data while  $z$  represents the value that  $Z$  takes;

Step 3: Estimate the quantity of demand for a COVID-19 vaccine: for each  $z \in \{1, \dots, \bar{z}\}$  and  $p \in w_Z^D$ ,  $\hat{q} = [1 - \hat{F}_{W|Z}(p)]\hat{\pi}_z 2L$ ;

Step 4: Choose the parameters of demand function ( $\beta$ ) to minimize the sum of squared errors between the quantities of demand and their estimates, that is  $\hat{\beta} =$

$\text{argmin} \sum_{j=1}^n (\hat{q}_j - q_j)^2$  where  $n$  is the number of observations in the estimation and  $n = \sum_{Z=1}^{\bar{Z}} |w_Z^D|$ .

In Step 1, by the Glivenko-Cantelli Theorem,  $\lim_{N \rightarrow \infty} \hat{F}_{W|Z}(p) = F_{W|Z}(p)$ . Similarly, the empirical PMF in Step 2 also converges to its underlying PMF. Consequently,  $\lim_{N \rightarrow \infty} \hat{q} = q$  in Step 3. In Step 4, if WTP is uniformly distributed, the empirical model, corresponding to equation (2), is as follows:

$$\hat{q}_j = \beta_0 + \sum_{z=2}^{\bar{z}} \beta_{z-1} d_{zj} - \beta_z p_j - \sum_{z=2}^{\bar{z}} \beta_{\bar{z}+z-1} d_{zj} \times p_j + \varepsilon_j \quad (5)$$

where the subscript  $j$  indexes observations for the estimation and  $j = 1, \dots, n$ ;  $d_z$  is a dummy variable, taking a value of one if  $Z = z$ , for  $z = 2, \dots, \bar{z}$ ;  $\hat{q}$  and  $p$  are the estimated quantity of demand and price respectively;  $\varepsilon$  is the error term; and  $\beta = (\beta_0 \ \dots \ \beta_{2\bar{z}-1})$  is a  $2\bar{z} \times 1$  vector of parameters to estimate.

Similarly, in light of equations (3) and (4), the empirical models corresponding to the exponential and Pareto distributions of WTP are respectively as follows:

$$\ln(\hat{q}_j) = \beta_0 + \sum_{z=2}^{\bar{z}} \beta_{z-1} d_{zj} - \beta_z p_j - \sum_{z=2}^{\bar{z}} \beta_{\bar{z}+z-1} d_{zj} \times p_j + \varepsilon_j \quad (6)$$

$$\ln(\hat{q}_j) = \beta_0 + \sum_{z=2}^{\bar{z}} \beta_{z-1} d_{zj} - \beta_z \ln(p_j) - \sum_{z=2}^{\bar{z}} \beta_{\bar{z}+z-1} d_{zj} \times \ln(p_j) + \varepsilon_j \quad (7)$$

Let the following matrixes collect the demand data:

$$\mathbf{X} = \begin{pmatrix} p_1 & d_{21} & \dots & d_{\bar{z}1} \\ p_2 & d_{22} & \dots & d_{\bar{z}2} \\ \vdots & \vdots & \ddots & \vdots \\ p_n & d_{2n} & \dots & d_{\bar{z}n} \end{pmatrix}, \hat{\mathbf{Y}} = \begin{pmatrix} \hat{q}_1 \\ \hat{q}_2 \\ \vdots \\ \hat{q}_n \end{pmatrix}, \mathbf{Y} = \begin{pmatrix} q_1 \\ q_2 \\ \vdots \\ q_n \end{pmatrix}, \boldsymbol{\varepsilon} = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

where if for equation (6), the elements of  $\hat{\mathbf{Y}}$  and  $\mathbf{Y}$  are in natural logarithm form, and if for equation (7), the column of price in  $\mathbf{X}$  is in natural logarithm form, in addition to the  $\hat{\mathbf{Y}}$  and  $\mathbf{Y}$ . Then, the ordinary least squares (OLS) estimator of  $\beta$  is  $\hat{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\hat{\mathbf{Y}}$ . As  $\lim_{N \rightarrow \infty} (\hat{\mathbf{Y}} - \mathbf{Y}) = 0$ ,  $\mathbf{X}$  by construction is asymptotically orthogonal to the error term  $\boldsymbol{\varepsilon}$ . Hence,  $\hat{\beta}$  is a consistent estimator of  $\beta$ . Nevertheless, unless we assume  $E[\boldsymbol{\varepsilon}] = 0$ ,  $\hat{\beta}$  is only asymptotically unbiased. The asymptotic variance-covariance matrix of  $\hat{\beta}$  is  $E[(\hat{\beta} - \beta)(\hat{\beta} - \beta)'] = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'E[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}']\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}$ . In order to compute the standard errors of  $\hat{\beta}$ , one can estimate  $E[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}']$  as in a regular OLS estimation. Alternatively, one can also use bootstrap to compute the standard errors.

Three remarks are warranted. First, in the OLS estimation, the number of observations ( $n$ ) is different from the sample size of WTP data ( $N$ ), despite they are related. As  $n = \sum_{Z=1}^{\bar{Z}} |w_Z^D|$ , it depends on the number of distinct values of WTP and the level of  $Z^2$ . For example, if  $Z$  is categorized into 8 levels and the WTP data contain 10 distinct values for each  $Z$ , then the sample size ( $n$ ) for OLS estimation is 80. The consistency of the estimator requires both  $n$  and  $N$  to be large. Second, in Step 3 with finite  $N$ ,  $\hat{q}$  contains estimation

<sup>2</sup> Note if for each  $Z$ , the number of distinct values of WTP are the same, then  $n = |w_Z^D|\bar{z}$ .

errors from Step 1. In Step 4,  $\hat{q}$  enters the regression as the dependent variable, where the errors are captured by  $\varepsilon$  in equations (5)-(7). Third, note the distributions of WTP and  $Z$  together determine the distribution of  $q$ , while the distribution of  $\hat{q}$  contains additional errors from Step 1. In the OLS estimation of equations (5)-(7), we do not need to assume  $\varepsilon$  to be normally distributed. However, we do need to assume that the WTP data,  $\{(w_i, z_i)\}_{i=1}^N$ , are independent and identically distributed, conditional on  $Z$ , such that the Glivenko-Cantelli Theorem applies.

#### 4. China

In this study, we estimate the demand functions for a COVID-19 vaccine in both China and the UAE. Choice of these two countries is based on availability of WTP data. The China WTP data are sourced from Qin et al. (2021), and the UAE WTP data are sourced from Muqattash et al. (2020).

From the WTP data, we construct the demand data (Steps 1-3 in Section 3), and then follow Step 4 to estimate the demand functions. We estimate three functional forms, namely the linear, semi-logarithmic linear and logarithmic linear models. In the estimations, we incorporate a set of dummy variables, generated from the discrete  $Z$  index, to allow the intercept and slope of price to vary across different categories of  $Z$ .

##### 4.1 The data

According to the World Health Organization (WHO), China registers more than 130 thousand confirmed cases of COVID-19 with 5,700 deaths from 3 January 2020 to 19 January 2022<sup>3</sup>. Since the outbreak of COVID-19, the Chinese government has been strict in controlling the spread of SARS-COV-2, utilizing such measures as locking down cities and vaccinations. A substantial amount of resources have been devoted to developing vaccines, resulting in successful development of at least five vaccines (see for example Hu and Chen, 2021). WHO has authorized emergency use of several Chinese developed vaccines, such as the Sinopharm vaccine. As of 7 January 2022, China has administered nearly 2.9 billion vaccine doses.

To investigate Chinese consumers' willingness to receive a COVID-19 vaccine and their WTP for the vaccine, Qin et al. (2021) commissioned a professional marketing research company to online survey Chinese consumers' attitude toward the COVID-19 vaccine from 11 to 13 March 2020, which includes a CVM to elicit consumers' WTP for the vaccine (unit: yuan/dose).

In the CVM, they adopted the payment card approach to elicit respondents' WTP. Specifically, they first provided information to respondents that the price of a flu vaccine is 50 yuan and the mortality rate of flue is 0.1%. Then they asked respondents to select the maximum acceptable price for a corona virus vaccine when the mortality rate of COVID-19 is 0.4%. Respondents' choices include seven ranges: 50–75 yuan, 75–100 yuan, 100–125 yuan, 125–150 yuan, 150–200 yuan, 200–250 yuan, 250–300 yuan, and above 300 yuan.

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<sup>3</sup> <https://covid19.who.int/region/wpro/country/cn>

In the survey, samples were randomly selected from a database of 2.6 million persons, and covers different provinces/cities. The survey also includes respondent characteristics, such as age, gender, monthly household income, and educational level. Qin et al. (2021) made their data publicly available at the publisher’s website.

Based on their estimated WTP data ( $N = 1,268$ ), we construct the demand data and estimate Chinese consumers’ demand function for a COVID-19 vaccine. For this purpose, first, we compare the distributions of WTP across different consumer characteristics by using the Kolmogorov-Smirnov (K-S) test, in order to construct the  $Z$  index. In their studies, Qin et al. (2021) regressed Chinese consumers’ WTP against consumer gender, age, educational level, income, and whether with children under 12 years old. They found that the coefficients for gender, whether with children under 12 years old, educational level (whether with less than 12 years’ education), age ( $\leq 24$  years old and  $\geq 55$  years old), and income (2000–3999 yuan and 4000–5999 yuan) are not statistically significant at the five per cent level, and the coefficients of age (35–44 years old and 45–54 years old) and income (6000–7999 yuan, 8000–9999 yuan, 10,000–14,999 yuan, and  $\geq 15,000$  yuan) are statistically significant at the five per cent level.

In light of their finding, we compare the WTP distributions by gender, educational level, whether with children  $< 12$  years old, age (35–54 years old), and income ( $\geq 6,000$  yuan)<sup>4</sup>. For the comparison by gender, the combined K-S test statistic is 0.0272, with a p-value of 0.975. Therefore, the WTP distribution does not exhibit significant differences by gender. The comparison of WTP distributions by whether with children  $< 12$  years old obtains a combined K-S statistic of 0.0629 with a p-value of 0.172, suggesting no significant difference. For the comparison by educational level, we obtain a combined K-S statistic of 0.2171 with a p-value  $< 0.001$ . Hence, the WTP distribution exhibits variations by educational level. Similarly, for the comparisons by age (35–54 years old) and income ( $\geq 6,000$  yuan), the combined K-S statistics are 0.1152 and 0.1755, both with a p-value  $\leq 0.001$ . Accordingly, we construct the  $Z$  index by grouping the respondents from three dimensions, namely educational level, age (35–54 years old) and income ( $\geq 6,000$  yuan), which results in  $Z$  taking eight values (namely  $Z \in \{1, 2, \dots, 8\}$ ).

Table 1 reports the definition of  $Z$  index and the distribution of sample by  $Z$  for the China data. For example, 190 responses (accounting for 14.98% of total responses) fall into the category of  $Z = 8$ , who has more than 12 years’ education, age between 35 and 54, and monthly household income higher than 6,000 yuan. Besides, the distribution of responses across  $Z$  appears sufficient for later estimations.

Figure 1 presents the distributions of WTP by  $Z$ . We can observe that the distributions exhibit substantial differences across different categories of  $Z$ , suggesting the distribution of WTP depends on  $Z$ . Besides, generally, there are more respondents who reported low values of WTP than those who reported high values of WTP. Hence, the WTP distribution more resembles the Pareto or exponential distributions.

Table 1. The  $Z$  index for China data

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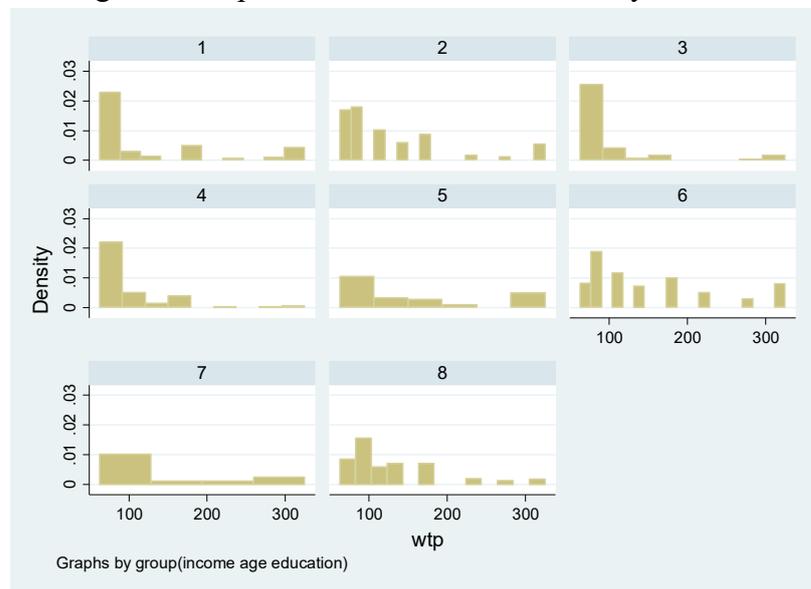
<sup>4</sup> We also use the K-S tests to compare the equality of WTP distributions conditional on income (8000-9999 yuan), income (10000-14999 yuan), and income ( $> 14999$  yuan) with that of income (6000-7999 yuan) respectively, which fail to reject the null hypothesis of equality.

Z	1( $\geq 12$ years' education)	1(income $\geq 6000$ )	1( $35 \leq$ age $\leq 54$ )	Freq.	%
1	0	0	0	115	9.07
2	1	0	0	346	27.29
3	0	0	1	98	7.73
4	1	0	1	87	6.86
5	0	1	0	41	3.23
6	1	1	0	367	28.94
7	0	1	1	24	1.89
8	1	1	1	190	14.98

Note: 1() is an indicator function;  $N = 1268$ .

Source: The author's estimation using data from Qin et al. (2021).

Figure 1. Empirical Distributions of WTP by Z, China



Source: The author's estimation using data from Qin et al. (2021).

The construction of demand data follows Steps 1-3 in Section 3, where the number of consumers ( $L$ ) is the population aged 15 and above in China in 2020 (1157.66 million according to National Bureau of Statistics, China). Table 2 reports the summary statistics for variables used in the OLS estimation of demand function in China. The variables exhibit substantial variations. For example, the sample averages of price and quantity are 172.541 yuan/dose and 84.26366 million doses respectively, with standard deviations of 88.7066 and 122.719 respectively. The sample size ( $n$ ) is 61, sufficient for the OLS estimation with 16 explanatory variables.

Table 2. Summary Statistics, China

Variable	Mean	Std. Dev.	Min	Max
$p$	172.541	88.7066	62.5	325
$q$	84.26366	122.719	0	593.4377
$d_2$	0.1311	0.3404	0	1
$d_3$	0.1148	0.3214	0	1
$d_4$	0.1311	0.3404	0	1

$d_5$	0.1148	0.3214	0	1
$d_6$	0.1311	0.3404	0	1
$d_7$	0.1148	0.3214	0	1
$d_8$	0.1311	0.3404	0	1

Note:  $n = 61$ ;  $p$ : price (unit: yuan/dose);  $q$ : quantity (unit: million doses);  $d_i = 1(Z = i)$ ,  $i = 2, \dots, 8$ .

Source: The author's estimation using WTP data from Qin et al. (2021)

#### 4.2 Demand in China

As observed in Table 5, the logarithmic linear demand function appears to fit the demand data better, with the highest  $R^2$ . Hence, the interpretation and later computation of consumer surplus are based on the logarithmic linear demand function<sup>5</sup>.

The coefficient of  $\ln(p)$  is estimated to be -1.1835, with a p-value  $< 0.001$ . Therefore, for Chinese consumers with  $Z = 1$  (namely those with less than 12 years' education, less than 6000 yuan monthly household income, and less than 35 years old or more than 54 years old), the price elasticity of demand for COVID-19 vaccine is 1.1835. Similarly, by combining the coefficient of  $\ln(p)$  and its interaction term with the dummy variables, we can calculate the price elasticities of demand for consumers with different  $Z$ s. With statistically non-significant coefficients ignored, we find the price elasticities of demand for consumers with  $Z = 2, 3, 4, 5, 6, 7$ , and  $8$  are 1.6042, 1.5590, 2.3862, 0.9445, 1.4322, 1.1835, and 2.1680 respectively.

The price elasticities of demand are all higher than one, except for consumers with  $Z = 5$ . Hence price subsidy can effectively promote COVID-19 vaccine take-up. With more recent development of the pandemic, for example the Delta and Omicron variants of SARS-COV-2, one may expect consumers to be inelastic towards the price change<sup>6</sup>. However, it shall be noted that the WTP data were collected in March 2020, when the pandemic was at an early stage and scientists just started developing the vaccines. A high elasticity possibly reflects consumers' uncertainty on the vaccines and the severity of the pandemic.

Table 5. Estimation Results, China

	[1] Linear		[2] Semi-log linear		[3] Log linear	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
<i>constant</i>	126.0102***	18.7834	5.1702***	0.1687	9.7772***	0.1823
$d_2$	306.5687***	82.1436	1.4468***	0.2597	3.0828***	0.3823
$d_3$	-60.2869**	25.9634	-0.6031	0.4276	0.9340	1.0086
$d_4$	-41.6183	29.6560	0.2244	0.2937	4.8810***	0.5570
$d_5$	-68.1726***	19.4899	-0.7981***	0.1942	-1.8443***	0.2360
$d_6$	454.7022***	81.8666	1.7080***	0.1978	2.6435***	0.4190
$d_7$	-94.5883***	19.2676	-1.2595***	0.2299	-0.5362	0.9109
$d_8$	133.1305**	54.1999	1.3360***	0.1984	5.0965***	0.8812

<sup>5</sup> Note the differences in  $R^2$  between the three models in Table 5 and later in Table 6 are small. So one may wish to use a model different from our interpretations here.

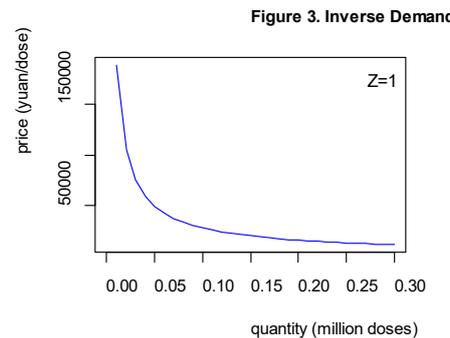
<sup>6</sup> We thank a reviewer for pointing this out.

$p$	-0.4123***	0.0803	-0.0079***	0.0010	-1.1835***	0.0405
$p \times d_2$	-1.0971***	0.3637	-0.0028	0.0017	-0.4208***	0.0824
$p \times d_3$	0.1839*	0.1096	-0.0020	0.0028	-0.3755*	0.2173
$p \times d_4$	0.0983	0.1301	-0.0082***	0.0020	-1.2028***	0.1154
$p \times d_5$	0.2244***	0.0839	0.0006	0.0013	0.2389***	0.0525
$p \times d_6$	-1.5549***	0.3643	-0.0019	0.0012	-0.2488***	0.0840
$p \times d_7$	0.3087***	0.0819	-0.0014	0.0013	-0.1961	0.1884
$p \times d_8$	-0.5286**	0.2489	-0.0071***	0.0013	-0.9845***	0.1724
$n$	61		53		53	
$R^2$	0.8883		0.9751		0.9871	
$F$	23.04		245.57		415.37	

Note: In [2], the dependent variable is  $\ln(q)$ ; In [3], the dependent variable is  $\ln(q)$  and in addition, price is in the natural logarithmic form ( $\ln(p)$ ); Sample size in [2] and [3] is smaller than that in [1] due to missing values created by taking logarithm of 0 quantity/price; Standard errors are robust; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Source: The author's estimation using data from Qin et al. (2021).

With the estimated demand functions, one can draw their graphs. For example, for consumers with  $Z = 1$ , the implied inverse demand function is  $p = 3872.1297 \times q^{-0.8450}$ . Figure 3 exhibits the graph. It can be observed that as price increases, the demand for COVID-19 vaccine rapidly drops, as consumers are price-elastic.



To investigate the impacts of education, income and age on the price elasticity of demand, we can compare the estimated coefficients of price and its interaction term. For example, when consumers have less than 12 years' education and age less than 35 or higher than 54, we can compare the estimate for  $Z = 1$  with that of  $Z = 5$  to obtain the impact of income. For  $Z = 1$  (< 12 years' education, income < 6,000 yuan, and age < 35 or > 54), the estimated demand function is  $\ln(q) = 9.7772 - 1.1835\ln(p)$ . In contrast, for  $Z = 5$  (< 12 years' education, income  $\geq 6,000$  yuan, and age < 35 or > 54), the estimated demand function is  $\ln(q) = 7.9329 - 0.9446\ln(p)$ . Hence, an income increase reduces the price elasticity of demand, which continues to hold in the other scenarios ( $Z = 2$  versus  $Z = 6$ ,  $Z = 3$  versus  $Z = 7$ , and  $Z = 4$  versus  $Z = 8$ ). Not surprisingly, higher income consumers are less sensitive to price change.

By a similar comparison, education appears to increase the price elasticity of demand, *ceteris paribus*. More educated consumers have a better capacity of understanding the vaccine development and pandemic situation. At an early stage when the vaccine is still under development, they appear to be more sensitive to price change. Compared with

consumers with age less than 35 or higher than 54, consumers aged between 35 and 54 appear to be more sensitive to price change (namely with higher price elasticity). This can occur as people aged between 35 and 54 may have less health concern, particularly compared with people aged above 54.

### 4.3 Consumer surplus

In order to compute the consumer surplus, we first assume that a COVID-19 vaccine is provided freely to consumers (namely  $p = 0$ ), which is consistent with reality. Then consumer surplus (CS) can be computed as  $CS = \sum_{z=1}^{\bar{z}} \int_{\underline{q}}^{\bar{q}} p_z(q) dq$ , where  $p_z(q)$  is the inverse demand function corresponding to  $Z = z$ ;  $\bar{q}$  is the level of demand if price is zero or  $\bar{q} = Pr(Z = z) \times L \times 2$  (the number of consumers with  $Z = z$  times two doses) for the logarithmic linear demand function; and  $\underline{q} = 0$  except for the demand function corresponding to  $Z = 5$  in China, where  $\underline{q} = 11.8222$  (the level of demand when  $p = 325$  yuan/dose) in order to ensure the integral is bounded. The computations of consumer surplus in China is as follows:

$$\begin{aligned}
 CS_{China} &= 3872.1297 \times \int_0^{209.9995} q^{-0.8450} dq + 3030.1432 \times \int_0^{631.8508} q^{-0.6234} dq \\
 &+ 529.2818 \times \int_0^{178.9742} q^{-0.6414} dq + 465.3638 \times \int_0^{158.8310} q^{-0.4191} dq \\
 &+ 4442.1228 \times \int_{11.8222}^{74.7848} q^{-1.0587} dq + 5839.5725 \times \int_0^{670.0536} q^{-0.6982} dq \\
 &+ 3872.1297 \times \int_0^{43.7595} q^{-0.8450} dq + 953.9391 \times \int_0^{346.8349} q^{-0.4613} dq \\
 &= 404.0438 \text{ billion yuan} = 58.5774 \text{ billion US\$}
 \end{aligned}$$

where in the last equality we use the annual average nominal exchange rate of Chinese yuan against US dollar in 2020 (6.8976 yuan/dollar) to convert to US\$.

## 5. UAE

### 5.1 The data

The WHO data suggest that UAE has more than 800 thousand confirmed cases of COVID-19 with almost 2,200 deaths from 3 January 2020 to 19 January 2022<sup>7</sup>. The UAE government has implemented a number of public health measures to tackle the COVID-19 disease, such as building field hospitals, providing rapid drive-through PCR testing, and promoting vaccination (see for example Alsuwaidi et al., 2021). On promoting vaccination, the UAE government provides free vaccines to its "medically eligible" residents through its

<sup>7</sup> <https://covid19.who.int/region/emro/country/ae>

National Vaccination Program (for details see Suliman et al., 2021). As of 17 January 2022, UAE has administered more than 23 million vaccine doses.

Muqattash et al. (2020) report a dataset of consumers' preferences of a COVID-19 vaccine in the UAE. They conducted a stated preference survey in the UAE to solicit WTP for a COVID-19 vaccine from 4 July to 4 August 2020, where the survey questionnaire is in a bilingual (Arabic and English) format and its design follows the guidelines of the WHO's SAGE working group. The survey was implemented in the Google Forms platform, and respondents were aged 18 years old and above, chosen by the snowball sampling method. The survey gathered 1,109 responses.

WTP data were collected via a question, "*what is the maximum amount of money (in dirham) you would be willing to pay for the COVID-19 vaccine, once discovered?*", which has seven options to choose, namely 0 AED, (0, 100AED], (100, 200AED], (200, 300AED], (300, 400AED], (400, 500AED], and > 500AED. For the purpose of estimating a demand function, we code interviewees' responses by the upper bound of the categories. For example, if a response is (100, 200AED], then the respondent's WTP is coded as 200AED. For a response of "> 500AED", we code it as 600AED. Such coding does not affect the estimation of empirical CDF of WTP, except for the response of "> 500AED" where the coding yields an under-estimation.

The dataset contains a rich array of information, including respondent characteristics such as gender, age, marital status, occupation, and monthly income. In constructing the  $Z$  index, we focus on these four characteristics and check whether the distribution of WTP varies across these characteristics by using the K-S test. In principle, one would like to include as many respondent characteristics as possible, which however will result in a curse of dimensionality. That is, as the number of respondent characteristics increases, the number of observations in each category of  $Z$  decreases, which in turn makes the estimation of conditional empirical CDF of WTP infeasible.

Age has four categories (18 to 25, 26 to 35, 36 to 45, and > 45). We compare the WTP distribution of one category with the distribution of the remaining categories sequentially, and find no evidence of significant differences. For example, the combined K-S test statistic for the comparison between the category of 18 to 25 and the rest is 0.0538, with a p-value of 0.864. Similarly for marital status, which has three categories (married, separated/divorced/widowed, and single), we also fail to find significant differences in the distribution of WTP across the three categories.

In contrast, gender (male and female) appears to significantly affect the distribution of WTP, with the K-S test statistic of 0.1604 and a p-value < 0.001. For occupation, it has five categories (not working, semi government, government, private, self-employed), and the sequential comparisons among the five categories find the WTP distributions of non-working and self-employed exhibit significant differences. As such we reclassify occupation into two groups, the non-working and self-employed versus the rest. The monthly income has five categories (None, less than 10,000 AED, less than 20,000 AED, less than 30,000 AED, and above 30,000 AED). The similar sequential comparisons find that the WTP distribution exhibits significant differences with monthly income higher than 10,000 AED. Accordingly, we re-classify the monthly income by the threshold of 10,000 AED. The K-S test obtains a

statistic of 0.1766 with a p-value  $< 0.001$ , confirming existence of significant differences of the WTP distributions.

Based on the K-S tests, we then construct the  $Z$  index by grouping the respondents from gender (male or female), occupation (whether not working or self-employed) and monthly income ( $> 10,000$  AED). The  $Z$  index thus takes eight levels ( $Z \in \{1,2, \dots, 8\}$ ), and Table 3 presents the definition of  $Z$  and sample distribution across  $Z$ . For example, 137 respondents are female, either self-employed or not working, and has a monthly income higher than 10,000 AED, which accounts for 12.35 per cent of total respondents. For each level of  $Z$ , the number of responses is sufficient for later estimation of conditional empirical CDF of WTP.

Table 3. The  $Z$  index for UAE data

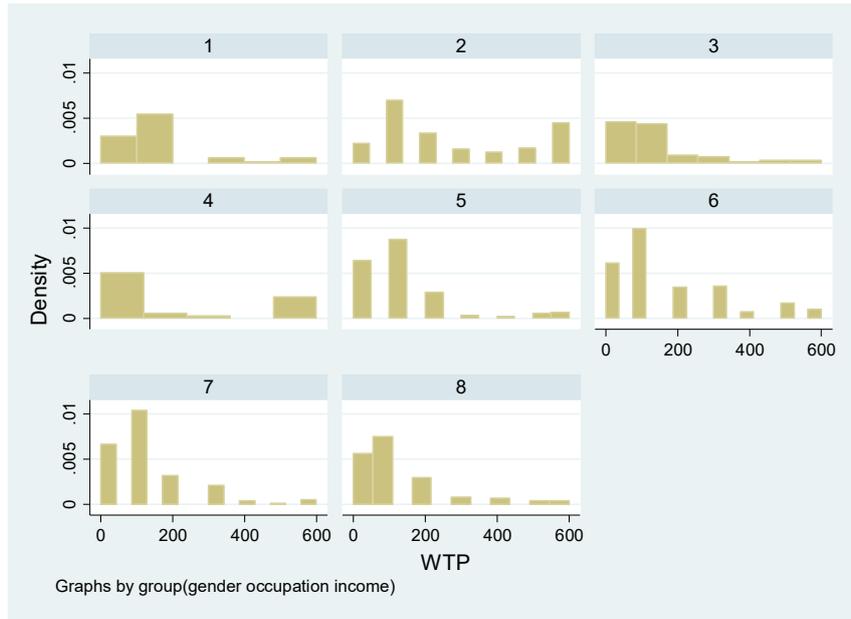
$Z$	$1(\text{gender} = \text{female})$	$1(\text{occupation} = \text{self-employed or not-working})$	$1(\text{income} > 10,000 \text{ AED})$	Freq.	%
1	0	0	0	46	4.15
2	0	0	1	174	15.69
3	0	1	0	61	5.5
4	0	1	1	28	2.52
5	1	0	0	165	14.88
6	1	0	1	277	24.98
7	1	1	0	221	19.93
8	1	1	1	137	12.35

Note:  $1()$  is an indicator function;  $N = 1109$ .

Source: The author's estimation using data from Muqattash et al. (2020)

Figure 2 reports the WTP distributions by  $Z$  in UAE. Similar to Figure 1, the WTP distributions exhibit substantial differences across different  $Z$ . Hence, it is necessary to condition on  $Z$  in estimating the empirical CDF of WTP. Besides, the conditional empirical CDFs also more resemble the exponential and Pareto distributions, rather than the uniform distribution.

Figure 2. Empirical Distributions of WTP by  $Z$ , UAE



Source: The author's estimation using data from Muqattash et al. (2020).

With data of WTP and  $Z$ , one can then construct the demand data, using Steps 1-3 in Section 3. The number of consumers is the population aged 15 and above in UAE in 2020 (8.4252 million, according to World Development Indicators). Table 4 presents the summary statistics of variables for the OLS estimation of demand function in UAE. The sample size ( $n$ ) is 54, sufficient for the estimation. It can be observed from Table 4 that there exist sufficient variations that allow us to estimate the demand function.

Table 4. Summary Statistics, UAE

Variable	Mean	Std. Dev.	Min	Max
$p$	300	204.6626	0	600
$q$	0.4944	0.7049	0	3.2364
$d_2$	0.1296	0.3390	0	1
$d_3$	0.1296	0.3390	0	1
$d_4$	0.1111	0.3172	0	1
$d_5$	0.1296	0.3390	0	1
$d_6$	0.1296	0.3390	0	1
$d_7$	0.1296	0.3390	0	1
$d_8$	0.1296	0.3390	0	1

Note:  $n = 54$ ;  $p$ : price (unit: AED/dose);  $q$ : quantity (unit: million doses);  $d_i = 1(Z = i)$ ,  $i = 2, \dots, 8$ .

Source: The author's estimation using WTP data from Muqattash et al. (2020).

## 5.2 Demand in UAE

Table 6 presents the UAE estimation results. Different from those of China, it appears that the semi-logarithmic linear functional form fits the demand data better, with a  $R^2$  of 0.9702. The logarithmic linear functional form also performs well in fitting the demand data, while in contrast the linear functional form is less satisfactory. Therefore, our interpretation and subsequent computation of consumer surplus are based on the semi-logarithmic linear demand function.

With the semi-logarithmic linear demand function, the price elasticity of demand is a linear function of price, namely  $\left|\frac{dq/q}{dp/p}\right| = -bp$ , where  $b$  is the slope of demand function. As can be observed in column [2] of Table 6, the coefficients of the interaction terms are not statistically significant at the five per cent level. Hence, the price elasticity of demand for a COVID-19 vaccine in the UAE appears not to significantly vary across different groups of consumers, while in contrast it increases with an increase of price. With a point estimate of the price coefficient being -0.0049 (p-value < 0.001), the price elasticities of demand can be calculated as 0.4865, 0.9731, 1.4596, 1.9461, 2.4327, and 2.9192 for  $p = 100, 200, 300, 400, 500,$  and  $600$  AED respectively. Hence for the purpose of promoting the COVID-19 vaccine take-up, a price subsidy when the price is high is more effective than when the price is low.

Comparing the price elasticities of demand in the UAE with those of China, two features emerge. First, the price elasticities are generally elastic in both countries. Second, in China the price elasticity of demand varies across different types of consumers, while in the UAE it varies across different levels of price. In light of such variations, it is likely that policymakers need to fine tune their setup of policies that are related to COVID-19 vaccines so as to achieve a better outcome.

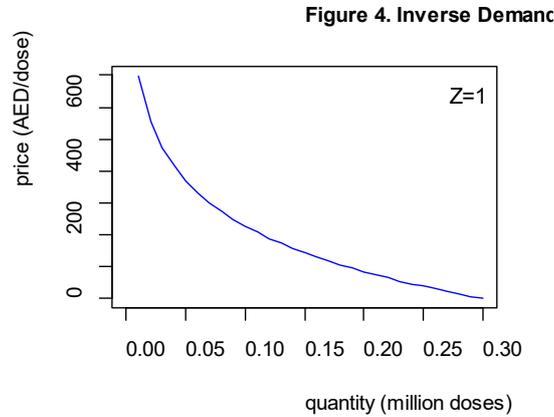
Table 6. Estimation Results, UAE

	[1] Linear		[2] Semi-log linear		[3] Log linear	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
<i>constant</i>	0.3206**	0.1326	-1.2039**	0.4667	1.0842*	0.5490
<i>d</i> <sub>2</sub>	1.7182***	0.2529	1.9592***	0.4738	2.1047***	0.7112
<i>d</i> <sub>3</sub>	0.0614	0.1741	0.3923	0.5009	2.7501**	1.2200
<i>d</i> <sub>4</sub>	-0.0527	0.1398	0.2268	0.5003	3.7516	3.1973
<i>d</i> <sub>5</sub>	0.7750*	0.4024	1.3429**	0.5540	3.2491***	0.8289
<i>d</i> <sub>6</sub>	2.1441***	0.4949	2.3676***	0.4711	5.7111***	1.7573
<i>d</i> <sub>7</sub>	1.2531**	0.5280	1.8659***	0.4970	6.5865***	0.9826
<i>d</i> <sub>8</sub>	0.6497*	0.3228	1.4065***	0.4842	5.4668***	1.1329
<i>p</i>	-0.0006**	0.0003	-0.0049***	0.0011	-0.7089***	0.1052
<i>p</i> × <i>d</i> <sub>2</sub>	-0.0027***	0.0006	0.0021*	0.0012	0.1195	0.1356
<i>p</i> × <i>d</i> <sub>3</sub>	-0.0001	0.0004	-0.0005	0.0012	-0.4266*	0.2264
<i>p</i> × <i>d</i> <sub>4</sub>	0.0001	0.0003	-0.0008	0.0015	-0.6391	0.6108
<i>p</i> × <i>d</i> <sub>5</sub>	-0.0016*	0.0009	-0.0005	0.0014	-0.3476**	0.1599
<i>p</i> × <i>d</i> <sub>6</sub>	-0.0042***	0.0012	-0.0007	0.0012	-0.6045*	0.3254
<i>p</i> × <i>d</i> <sub>7</sub>	-0.0027**	0.0013	-0.0024*	0.0014	-0.9482***	0.1721
<i>p</i> × <i>d</i> <sub>8</sub>	-0.0014*	0.0008	-0.0018	0.0012	-0.7977***	0.2137
<i>n</i>	54		46		38	
<i>R</i> <sup>2</sup>	0.8393		0.9702		0.9559	
<i>F</i>	14.14		316.25		141.57	

Note: In [2], the dependent variable is ln(q); In [3], the dependent variable is ln(q) and in addition, price is in the natural logarithmic form (ln(p)); Sample size in [2] and [3] is smaller than that in [1] due to missing values created by taking logarithm of 0 quantity/price; Standard errors are robust; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Source: The author's estimation using data from Muqattash et al. (2020).

Similar to Figure 3, one can draw the graphs of the demand functions in the UAE. Figure 4 presents the graph of inverse demand function ( $p = -247.452 + 205.5372 \times \ln(q)$ ) for consumers in UAE with  $Z = 1$ . Note that as the price of a COVID-19 vaccine drops to zero, UAE consumers of type  $Z = 1$  are willing to purchase 3.3332 million doses.



### 5.3 Consumer surplus

Similar to Section 4.3, the consumer surplus in UAE can be computed as follows:

$$\begin{aligned}
 CS_{UAE} &= 3 \times \int_0^{0.3000} (-247.452 - 205.537 \ln(q)) dq + \int_0^{2.1282} (275.1512 - 364.299 \ln(q)) dq \\
 &\quad + \int_0^{1.1491} (28.5682 - 205.537 \ln(q)) dq \\
 &\quad + \int_0^{3.2018} (239.1842 - 205.537 \ln(q)) dq \\
 &\quad + \int_0^{1.9386} (91.6767 - 138.491 \ln(q)) dq + \int_0^{1.2245} (41.6283 - 205.537 \ln(q)) dq \\
 &= 2374.7304 \text{ million AED} = 646.6250 \text{ million US\$}
 \end{aligned}$$

where in the last equality we use the exchange rate (3.6725 AED/US\$) reported in Muqattash et al. (2020) to convert to US dollar.

The consumer surplus of around 58.58 billion US\$ and 646.63 million US\$ in China and UAE respectively is sizeable. The figures are obtained, assuming the governments of China and UAE provide the COVID-19 vaccine freely to their citizens (aged 15 and above). Policymakers can compare the consumer surplus with the costs of vaccine purchase and provision in assessing their COVID-19 vaccine program. Nevertheless, it shall be noted that the computed consumer surplus is private benefit and does not account for the positive externality of vaccination, namely as more people are vaccinated it becomes more difficult for the SARS-COV-2 to spread.

## 6. Limitations and Future Work

Knowledge of demand for a COVID-19 vaccine and the associated consumer surplus is meaningful as it can help policymakers in assessing their COVID-19 vaccine programs. In this study, we explicitly estimate demand for a COVID-19 vaccine. To the best of our knowledge, this is the first attempt in the existing literature. Hence, this study can serve as a point of comparison for future work. In addition, a number of limitations in this study are worth of noting, namely the representativeness of survey data, treatment of different types of COVID-19 vaccines, and the shortcomings of the CVM.

First, the surveys of Qin et al. (2021) and Muqattash et al. (2020) gathered less than 1,500 responses. It is unclear to what degree the surveys can represent the populations of China and UAE. Indeed, as noted by Qin et al. (2021), their survey may not represent China's population accurately as people with a low educational level and the elderly are less likely to respond to the online survey. Besides, consumers' WTP for a COVID-19 vaccine is likely to vary across time, depending on such factors as how the pandemic unfolds, the restrictions imposed by governments and vaccination plans<sup>8</sup>. Due to data availability, we are not able to account for such dynamics in this study. With availability of WTP data for COVID-19 vaccines in other countries and at a different time, particularly those that account for variation of WTP across time, future work can estimate the demand function and consumer surplus in these countries and time frame. In addition, one can also design surveys to gather WTP data, which provides greater degree of freedom in the research design.

Second, in this study, we treat different types of COVID-19 vaccines as perfect substitute to each other. Consumers are likely to have different WTP for different types of vaccines. To account for such a situation, in collecting the WTP data, one will need to build the types of vaccines into the survey design. In reality, consumers may not have a sufficient degree of freedom to choose which type of vaccines, though they can shop around for a vaccination place that offers a desired type<sup>9</sup>. Hence, this limitation is less of concern.

Third, Qin et al. (2021) and Muqattash et al. (2020) utilized the CVM to solicit consumers' WTP. The CVM is an approach extensively used to solicit WTP in a hypothetical context, and a number of researchers have provided detailed guidelines on conducting CVM (see, for example, among others Carson, 2000, 2012; Carson and Hanemann, 2005; Mitchell and Carson, 1989). In the health field, the CVM is also widely used (for example to name a few Bobinac et al., 2012; Guerriero et al., 2018; Mataria et al., 2004; Mussio et al., 2021; Pinto-Prades et al., 2009; Smith, 2003).

That said, bias is likely to exist in the CVM. In particular, the CVM works in a hypothetical context, where respondents are likely to over-report their WTP, resulting in a hypothetical bias. For example, Blumenschein et al. (2001) find that the CVM overestimates WTP, in comparing hypothetical and real purchase decisions for an asthma management program among 172 asthma patients in the US. Ryan et al. (2017) similarly find that hypothetical WTP is higher than actual WTP. In light of the hypothetical bias, our estimate of consumer surplus is an upper bound of the actual consumer surplus. In addition, future work

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<sup>8</sup> We thank a reviewer for pointing this out.

<sup>9</sup> We thank a reviewer for pointing this out.

can adopt measures to reduce the hypothetical bias, for example by combining the stated and revealed preference data as suggested by Buckell and Hess (2019) and de Corte et al. (2021).

## 7. Concluding Remarks

Taking consumers' WTP as the primitive, this study first establishes an analytical framework for demand estimation. The demand function we establish is analytically simple, and reduces to commonly used functional forms under specific distributions of WTP. For example, a uniform distribution of WTP results in a linear demand function. The estimator we propose is asymptotically consistent, as the error term is asymptotically orthogonal to the right-hand-side variables, including price. By construction, the estimator also guarantees the Law of Demand is satisfied.

We apply the analytical framework to estimate the demand functions for a COVID-19 vaccine in China and the UAE, utilizing the WTP data from Qin et al. (2021) and Muqattash et al. (2020). We find that the price elasticities of demand are mostly larger than one in both countries. In China, the price elasticities of demand depend on consumer characteristics, and is ranged between 0.9445 and 2.3862. In the UAE, the price elasticities of demand depend on the price level linearly, and is ranged between 0.4865 and 2.9192. The consumer surplus we calculate is sizeable, with around 58 billion US\$ (400 billion Chinese yuan) in China and 646 million US\$ (2,374 million AED) in the UAE. These figures can help policymakers to assess their vaccine programs.

As discussed in Section 6, our analysis is not without limitations. For future work, researchers can try to improve the representativeness of their surveys in eliciting consumers' WTP for COVID-19 vaccines, and build in the vaccine characteristics in the surveys which is likely to result in a richer set of findings. Our analysis takes the WTP data as the input. Researchers frequently employ the CVM to solicit consumers' WTP. Despite of its popularity, the CVM exhibits some bias, such as the hypothetical bias. In the future, researchers who intend to collect WTP data by using the CVM need to adopt measures to reduce such bias. Besides, the WTP data can also be collected via other methods, such as the conjoint analysis and auction.

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