Determinants of non-cash payments in Asian countries

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Abstract. Non-cash payments, such as payment cards and digital payment, are more efficient ways to complete transactions when compared to cash payment. This study investigates the factors that influence the use of non-cash payments in 10 Asian countries, namely China, India, Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Thailand, and Vietnam. A panel data is used in this study and the period 2016-2017 is considered. To address the ill-posed problem caused by limited observations, generalized maximum entropy (GME) estimator is employed. The purposes of the study are to identify the cross-country determinants of non-cash payments and prove that GME estimator is the most effective estimation method. The results of data show that online banking penetration and debit card penetration are important factors boosting non-cash payments. In addition, the sales of desktop-PCs and the number of individuals who overed 35 years are the determinants of non-cash payments.

1. Introduction
The rapid growth of science and technology have transformed the way people communicate and transact around the world. Non-cash payments such as payment cards as well as digital payment are more efficient ways to complete transactions when compared to cash. Digital payments are defined as non-cash transactions processed through digital channels which main form is mobile payment. Mobile payment means that all transactions at the point-of-sale in retail locations processed via personal smart devices. In recent years, mobile payments are widely used and are proved to be an effective way to make a transaction. The mobile Point of Sale (POS) payment users in Asian dominated 715.6 million compared with 799.1 million users in the world 2017. This fact shows that mobile payments perform efficiently in Asia as it eliminates the limitation of distance between the region and its real-time process in which the users can check, transfer or make consumption on the account at anytime and anywhere. The most important factor is that the development of non-cash payment allows for lowering the costs of money circulation and thereby leads to significant economic gains.

In the literature, researchers have been committed to the analysis of determinants of these development by using Structural Equation Model (SEM), Technology Acceptance Model (TAM), and Unified Theory of Acceptance and Use of Technology (UTAUT), little attention has been paid to the analysis of determinants by integrating macroeconomic data through cross-country.

Therefore, the aim of this paper is to investigate cross-country determinants of digital payments based on the panel data of 10 Asian countries including China, India, Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Thailand, and Vietnam during 2016-2017. As the data in this study is limited and it may have a high degree of collinearity, thus if a traditional statistical method was used, likes ordinary least squares and maximum likelihood, the results are obviously not reliable. To overcome this limitation, a Generalized Maximum Entropy (GME) estimator is employed for panel
data regression model by Song, and Cheon [1]. Two possible measures considered the total transaction value in mobile POS payments and the number of mobile POS payments were investigated to explain the determinants of non-cash payments in Asian countries. GME estimation for panel data regression model was employed to regress these measures on selected explanatory variables such as sales of mobile phones, sales of laptops, sales of desktop-PCs, smartphone penetration, population, infrastructures, and finance.

The paper is organized as follows: Section 2 presents a review of the literature on non-cash payment and panel data. Section 3 presents the data and some preliminary analysis needed for correct estimation of GME estimation for panel data regression model. Section 4 outlines the results. The conclusions to the research questions are given in the last part.

2. Literature reviews

In recent years, researchers have shifted their focus of non-cash payments from payment cards to digital payment. Zhang YL, Sun J, Yang ZJ and Wang Y [2] found that culture, subjective norm, and socioeconomic status and main personal characteristics including demographics, personality traits, and past behavior have direct and moderating effects on mobile acceptance and usage. Lu J, Wei J, Yu CS and Liu C [3] revealed that post-usage privacy protection and social influence beliefs drove user continuous intentions direct towards mobile payments. Shakir S, Akhtar M and Safiuddin S [4] pointed out the market drivers in digital payments for rural India were government policies and the increase in credit cards issuance. Kathleen A [5] find out the unbanked population limited the development of cashless in Indonesia. Łukasz Goczek and Bartosz Witkowski [6] studied the determinants of retail card payments by using cross-country panel data. They employed microdata logit model and tow macrodata methods which are the System GMM Blundell-Bond (1998) estimator and the Kiviet (1995) LSDV estimator. The study found that trust was positively related to card payment value. Jonker N, Plooij M and Verburg J [7] studied the consumer payment behavior by direct payment data and the results show positive effects of the national campaign to promote debit card usage, both in the short and in the long run. Tao Z [8] studied the determinants of mobile payment continuance usage by using structural equation modelling (SEM) from a survey questionnaire, and the results indicated that performance expectancy, trust in mobile payment and flow affect continuance usage.

3. Methodology and data

When dealing with data with ill-posed problem, the Generalized Maximum Entropy (GME) is found to provide a robust estimate than least square, maximum likelihood or GMM when one facing multicollinearity, poor model specification and small data size by Song and Cheon [1].

3.1. Panel data regression model

\[ y_{nt} = x'_{nt} \beta + u_{nt}, n = 1, ..., N; t = 1, ..., T, \]

where \( n \) denotes one of 10 Asian countries, \( t \) denotes 2 years in the sample, \( y_{nt} \) is the value of one of the two non-cash payment measures (two dependent variables). \( x'_{nt} \) is a \( K \times 1 \) vectors of characteristics measured during or at the start of the period. \( \beta \) denotes the \( K \times 1 \) vectors of regression coefficients. \( u_{nt} \) is the regression disturbance. The prime symbol also indicates the transpose of a matrix or vector. \( \mu_n \) denotes the nth individual specific effects assumed to be i.i.d. \( (0, \sigma^2) \) and \( \epsilon_{nt} \) is the remainder disturbance assumed to be i.i.d. \( (0, \sigma^2) \) which is independent of \( \mu_n \).

Then the equation (1) can be written in matrix notation as

\[ y = X\beta + u, \]

where \( y \) is now of dimension \( NT \times 1 \), \( X \) is \( NT \times K \) where the constant is absorb into \( X \), \( \beta \) is \( K \times 1 \), and \( u \) is \( NT \times 1 \). The error term \( u \) can be written as

\[ u = (I_N \otimes \iota_T) \mu + \varepsilon, \]
with \( u' = (u_{1}, \ldots, u_{T}, \ldots, u_{N_{1}}, \ldots, u_{N_{T}}) \), \( \mu' = (\mu_{1}, \ldots, \mu_{N}) \), and \( \varepsilon' = (\varepsilon_{1}, \ldots, \varepsilon_{T}, \ldots, \varepsilon_{N_{1}}, \ldots, \varepsilon_{N_{T}}) \) where \( I_{N} \) is an \( N \times N \) identity matrix, \( i_{T} \) is a \( T \times 1 \) vector of ones, and \( \otimes \) denotes the Kronecker product.

### 3.2. The Generalized Maximum Entropy Model (GME)

We describe the GME methodology for a panel data regression model, introduced by Song and Cheon [1]. First, let reparametrize \( \beta \) and \( u \) in (2) as in Judge and Golan [9].

\[
\beta = Zp = \begin{bmatrix}
Z_{1}' & 0 & \cdots & 0 \\
0 & Z_{2}' & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & Z_{K}'
\end{bmatrix}
\begin{bmatrix}
p_{1} \\
p_{2} \\
\vdots \\
p_{K}
\end{bmatrix},
\tag{4}
\]

where \( Z \) is a \( K \times KM \) matrix, \( p \) is a \( KM \times 1 \) vector, \( \beta_{k} = \sum m Z_{m,k} \) for every \( k \), \( Z_{k}' = (Z_{k1}, \ldots, Z_{kM}) \), and \( p_{k}' = (p_{k1}, \ldots, p_{kM}) \).

\[
\mu = Fg = \begin{bmatrix}
f_{1}' & 0 & \cdots & 0 \\
0 & f_{2}' & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & f_{N}'
\end{bmatrix}
\begin{bmatrix}
g_{1} \\
g_{2} \\
\vdots \\
g_{N}
\end{bmatrix},
\tag{5}
\]

where \( F \) is a \( N \times NR \) matrix, \( g \) is a \( NR \times 1 \) vector, \( \mu_{n} = \sum r f_{nr} g_{nr} \) for every \( n \), \( f_{n}' = (f_{n1}, \ldots, f_{nR}) \), and \( g_{n}' = (g_{n1}, \ldots, g_{nR}) \). Moreover,

\[
\varepsilon = Vw = \begin{bmatrix}
v_{11}' & 0 & \cdots & 0 \\
0 & v_{12}' & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & v_{NT}'
\end{bmatrix}
\begin{bmatrix}
w_{11} \\
w_{12} \\
\vdots \\
w_{NT}
\end{bmatrix},
\tag{6}
\]

where \( V \) is a \( NT \times NTJ \) matrix, \( w \) is a \( NTJ \times 1 \) vector, \( \varepsilon_{nt} = \sum j v_{ntj} w_{ntj} \) for every \( n \) and \( t \), \( v_{nt} = (v_{nt1}, \ldots, v_{ntJ}) \), and \( w_{nt} = (w_{nt1}, \ldots, w_{ntJ}) \).

Then, we can rewrite (2) as a generic linear model

\[ y = X\beta + u = XZp + (I_{N} \otimes i_{T})Fg + Vw. \tag{7} \]

Therefore, the generic GME problem selects \( p, g, w \) to maximize

\[ H(p, g, w) = -p' \log(p) - g' \log(g) - w' \log(w), \tag{8} \]

Subject to \( i_{K} = (I_{K} \otimes i_{M}), i_{N} = (I_{N} \otimes i_{R})g \) and \( i_{NT} = (I_{NT} \otimes i_{J})w \).

Then, the Lagrangian function is

\[
L = -P \log(p) - G \log(g) - W \log(w) + \lambda [y - XZp - (I_{N} \otimes i_{T})Fg - Vw] \\
+ \theta [i_{K} - (I_{K} \otimes i_{M})P] + \gamma [i_{N} - (I_{N} \otimes i_{R})g] + \tau [i_{NT} - (I_{NT} \otimes i_{J})w]
\]

Taking the gradient to derive the first-order conditions, we have

\[
\nabla_{p} L = -\log(p) - i_{KM} - Z'X'\lambda - (I_{K} \otimes i_{M})\theta = 0, \\
\nabla_{g} L = -\log(g) - i_{NR} - F'(I_{N} \otimes i_{T})\lambda - (I_{N} \otimes i_{R})\gamma = 0,
\]

3
\[ \nabla_w L = -\log(w) - i_{NTJ} - V' \lambda - (I_{NT} \otimes i_{j}) \tau = 0, \]
\[ \nabla_{\lambda} L = y - XZp - (I_N \otimes i_{p}) Fg - VW = 0, \]
\[ \nabla_{p} L = i_K - (I_K \otimes i_M) p = 0, \]
\[ \nabla_{g} L = i_N - (I_N \otimes i_R) g = 0, \]
\[ \nabla_{\tau} L = i_{NT} - (I_{NT} \otimes i_{j}) w = 0. \]

After some algebra, we obtain
\[ p = \exp(-Z'X'\lambda') \odot \exp[-i_{KM} - (I_K \otimes i_M) \theta], \]
\[ g = \exp(-F'(I_N \otimes i_R') \lambda') \odot \exp[-i_{NR} - (I_N \otimes i_R) \gamma], \]
\[ w = \exp(-V' \lambda') \odot \exp[-i_{NTJ} - (I_{NT} \otimes i_{j}) \tau], \]

where \( \odot \) denotes the Hadamard product.

### 3.3. Data

The panel data regression model is used to analyse the determinants of non-cash payments in 10 Asian countries, consisting of China, India, Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Thailand, and Vietnam. The sample period of 2 years, from 2016 to 2017 are collected and the data is obtained from Statista database. The factors affecting variables are provided in the Table 1.

| Name                           | Definition                                                                 | Value |
|--------------------------------|---------------------------------------------------------------------------|-------|
| Mobile phones / capita in units | average per capita sales of mobile phones in units                        | x1    |
| Laptops volume / capita in units | average per capita sales of laptops and tablets in units                  | x2    |
| Desktops-PCs volume / capita in units | average per capita sales of desktop-PCs in units | x3    |
| Population                     | 0-34 years: number of individuals (age 0-34) living in the selected region | x4    |
|                                | 35-55+ years: number of individuals (age 35-55+) living in the selected region | x5    |
| Infrastructure                 | Smartphone penetration in % penetration of individuals from the total population using a smartphone on a monthly basis | x6    |
|                                | Internet penetration in % percentage of individuals from the total population using the Internet on a monthly basis | x7    |
|                                | Average connection speed in kbits/s average Internet connection speed in kbits/s | x8    |
| Finance                        | Online banking penetration in % penetration of individuals (total population over 16 years) using online-banking services at least once a year (e.g. bank transfers, account information) | x9    |
|                                | Debit card penetration in % percentage of individuals (total population over 16 years) who own at least one debit card | x10   |

Source: own.

The following model is used to estimate determinants of non-cash payments in 10 Asian countries:

\[ y_{nt} = \alpha_0 + \sum_{j=1}^{10} \beta_j x_{jnt} + \gamma_n + \epsilon_{nt}, \]

where \( n \) denotes one of 10 Asia countries, \( t \) denotes 2 years in the sample, \( y_{nt} \) is the non-cash payment measure (the total value in mobile POS payments, the number of mobile POS payments), \( x_{jnt} \) is a
vector of independent variables (independent variables listed in Table 1). $\beta_j$, for $j = 1,2, \cdots, 10$ are the regression coefficients. $\alpha_0$ is a constant term. $\gamma_n$ is the unobserved country-specific effects, $\epsilon_{nt}$ is the i.i.d error term.

In this study, two equations are estimated where each equation relate to the different dependent variables:
1. The total transaction value in mobile POS payments,
2. The number of mobile POS payments.

4. Results
The study aims to identify the determinants of non-cash payments. Prior to interpret the results, a variance inflation factor (VIF) is conducted to test the existence of the multicollinearity problem in the Panel regression model. Then, the performance of GME estimator examined by comparing with the conventional Pooled OLS. To make the comparison, the Mean Squared Error (MSE) value is employed and the lower MSE indicates the better performance.

4.1. Testing for multicollinearity
Normally, the more variables are used in the models the more degree of multicollinearity increases, as such the regression model estimates of coefficients become unstable and standard errors for coefficients can get significantly inflated. Since the data in this study is limited and it may have a high degree of collinearity, it is better to test for multicollinearity. This test will be done with “VIF” index. VIF means variance inflation factor. Results for VIF test are listed in Table 2. From the result, there is a multicollinearity for variable X1, X2, and X4. So, to avoid the multicollinearity problem, these three variables are deleted out form the empirical models.

| Table 2. Multicollinearity test-VIF. (variance inflation factor) |
|-------------------|---------|---------|
| Variables          | VIF     | Klein   |
| X1: mobile phones  | 1290.96 | 1       |
| X2: laptops volume | 1081.54 | 1       |
| X3: desktop-PCs volume | 16.07 | 0       |
| X4: 0-34 years     | 195.50  | 1       |
| X5: 35-55+ years   | 107.99  | 0       |
| X6: smartphone pene| 18.30   | 0       |
| X7: Internet pene  | 11.66   | 0       |
| X8: connection speed| 13.87  | 0       |
| X9: online banking pene | 31.52 | 0       |
| X10: debit card pene| 7.13   | 0       |

Source: calculation. Notes: 1 means that collinearity is detected by the test; 0 means that collinearity is not detected by the test.

4.2. The total transaction value in mobile POS payments equation
Prior we interpret the results, GME estimator is found perform better than traditional Pooled OLS as the lower MSE value is obtained for both equations. This result indicate the superior of GME over the OLS estimator and confirm the higher accuracy of our estimation in the empirical study.

The estimated results for the total transaction value are summarized in Table 3. The model is fitted using panel data of 10 Asian countries over 2 years period from 2016 to 2017. Most estimated coefficients have signs which were reasonable with economic intuition. Variables ‘online banking pene’ and ‘debit card pene’ have positive effect on the response variable and show a highly significant since p-value is very small and close to zero. Past references indicated that irrespective of the device and payment service provider, mobile payment devices are registered with their banks thereby enabling high security transfer of funds from the payer’s bank (or credit card account) to the payee’s
bank account by way of a few key presses on the mobile device by Ng and Yip [10]. The findings of Elisa [11] showed that one of the key drivers of mobile payment adoption is the developed financial infrastructure. India government has tried to issue credit cards to farmers. This activity drives in terms of enabling POS solutions to rural merchants has created fundamental platform that is essential for gaining momentum of digital payments in the rural segment, Shakir, S. Akhtar, M. and Safiuddin, S [4]. While the unbanked population limited the development of cashless in Indonesia, Kathleen, A [5]. The above findings prove that ‘online banking pene’ and ‘debit card pene’ are two important determinants of mobile payments.

In addition, Desktop-PCs variable also has a positive influence to the transaction value of mobile payments. Likewise, variable 35-55 years shows a positive and significant effect on the transaction value. However, another three factors, namely Internet penetration, connection speed, and Smartphone pene, are not significantly influence the transaction value in mobile POS payments.

| Table 3. Results of the total transaction value in mobile POS payments. |
|---------------------------------------------------------------|
| **Coefficient** | **Standard Error** | **P-value** |
| Desktop-PCs volume | 0.02 | 0.006 | 0.004*** |
| 35-55+ years | 0.02 | 0.009 | 0.007*** |
| Smartphone pene | -0.07 | 0.020 | 0.485 |
| Internet pene | 0.04 | 0.021 | 0.067 |
| Connection speed | -0.01 | 0.023 | 0.516 |
| Online banking pene | 0.10 | 0.015 | 0.000*** |
| Debit card pene | 0.04 | 0.010 | 0.000*** |

MSE (GME) 0.00185  MSE (Pooled OLS) 800.671
Source: calculation. Notes: *p < 0.01,**p < 0.001,***p < 0

| Table 4. Results of the number of mobile POS payments users. |
|---------------------------------------------------------------|
| **Coefficient** | **Standard Error** | **P-value** |
| Desktop-PCs volume | 0.01 | 0.003 | 0.002** |
| 35-55+ years | 0.01 | 0.005 | 0.007** |
| Smartphone pene | -0.03 | 0.010 | 0.999 |
| Internet pene | 0.01 | 0.005 | 0.055* |
| Connection speed | 0.00 | 0.006 | 0.878 |
| Online banking pene | 0.05 | 0.008 | 0.000*** |
| Debit card pene | 0.02 | 0.005 | 0.000*** |

MSE (GME) 0.00028  MSE (Pooled OLS) 647.236
Source: calculation. Notes: *p < 0.01,**p < 0.001,***p < 0

4.3. The number of mobile POS payments users
The determinants of the number of mobile POS payments users are summarized in Table 4. It is similar to the case of the transaction value. ‘Online banking pene’ and ‘Debit card pene’ have positive effects on the response variable and show highly significant. Variables Desktop-PCs volume, 35-55+ years, and Internet penetration are positively and significantly influence to the number of users as well. Connection speed and Smartphone phone penetration are not significantly impacted the number of mobile POS payments users. Different for the first equation, we can obtain the significant impact of Internet pene on the number of mobile.

5. Conclusions
This study examined some of the possible factors that determined the use of non-cash payments in 10 Asian countries, namely, China, India, Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Thailand, and Vietnam. A panel regression model was used taking the period 2016-2017. To
solve the ill-posed problem of data, a Generalized Maximum Entropy (GME) estimator is employed and consider a transaction value and number of users as the dependent variables. The results show that our GME estimator perform better than the convention estimator.

In the empirical results, we find that the online banking penetration and debit card penetration are key statistically and economically significant determinants of the non-cash payments. Moreover, it is important that these countries should adopt related measures and policies to promote the development of non-cash payment in the future; government should support financial infrastructure development; government banks and companies could try to improve financial technology.

References

[1] Song S H and Cheon S Y 2006 A study of generalized maximum entropy estimator for the panel regression model *Korean Journal of Applied Statistics* **19**(3) 521-534

[2] Zhang Y L, Sun J, Yang Z J and Wang Y 2018 What makes people actually embrace or shunt mobile payment: a cross-culture study *Mobile information systems* doi:10.1155/2018/7497545

[3] Lu J, Wei J, Yu C S and Liu C 2017 How do post-usage factors and espoused culture values impact mobile payment continuation? *Behaviour & information technology* **36**(2) 140-164

[4] Shakir S, Akhtar M and Safiuddin S 2017 Digital payments for rural India-challenges and opportunities *International journal of management and applied science* ISSN: 2394-7926

[5] Kathleen A 2016 Cashless in Indonesia: Gelling mobile e-frictions *Journal of southeast Asian economies* Vol. 33, No. 3 pp. 364-86

[6] Goczek Ł and Witkowski B 2015 Determinants of card payments *Applied economics* **48**(16) 1530-1543. doi:10.1080/00036846.2015.1102846

[7] Jonker N, Plooij M and Verburg J 2015 Does a Public Campaign Influence Debit Card Usage? Evidence from the Netherlands *SSRN Electronic Journal* doi:10.2139/ssrn.2596538

[8] Tao Z 2014 Understanding the determinants of mobile payment continuance usage *Industrial Management & Data Systems* **114**(6) 936-948 doi:10.1108/imds-02-2014-0068

[9] Judge G and Golan A 1992 Recovering information in the case of ill-posed inverse problems with noise, University of California at Berkeley, Unpublished paper

[10] Ng I C L and Yip N K T 2010 Theoretical foundation in the pricing of intermediating services: the case of payments via mobile phones *Journal of revenue and pricing management* Vol. 9 No. 3 pp. 217-227

[11] Elisa T 2015 A case study in mobile: paving the way for mobile payments in Thailand. Retrieved from https://www.bostonfed.org/publications/payment-strategies/a-case-study-in-mobile-paving-the-way-for-mobile-payments-in-thailand.aspx