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The role of Fintech e-payment on APEC economic development

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Abstract. The goal of this study is to investigate whether Fintech e-payment affects economic development in APEC countries, in particular, income growth, productivity, price volatility, and income inequality. We use e-payment index introduced by RMIT University and TRPC and apply quantile regression with GME approach. We consider the quantile level at 0.25, 0.50, and 0.75. At the low level of economic development variables, the Fintech have the highest effects on these variables compared with the medium and high level of economic development. In other words, Fintech supports not only low level of growth and productivity but also reduce the low level of price volatility and income inequity. Further investigation provides that e-payment usage and technology empowerment are helpful to economic development, particularly, increasing in growth and productivity.

1. Introduction
Technology has always played a vital role in the financial sector in the past decades. It began in 1950 when the first financial technology (Fintech) was introduced to ease the burden of carrying cash, known as credit card followed using automated teller machines (ATMs) to replace bank tellers and branches in the 1960s. Then, in the 1970s, electronic stock trading began on exchange trading floors and the Internet and e-commerce business models shined in the 1990s. In the early 21st century, once again, Fintech has completely changed the role of the financial services. The term “Fintech” refers to the technologies that can be used in financial sector to help traditional companies form innovative solutions such as mobile internet, big data, cloud computing, and the blockchain. Nowadays, there are several Fintech innovations launched and they have changed the ways of trading and banking, for instance, digital wallets, payment apps, mobile banking, mobile trading, robo-advisor sites, and peer-to-peer lending sites.

Using Fintech, businesses can develop new products and services by interrogating the information and insights from customers. Additionally, Fintech can help all businesses through improved payments systems, customer relationship management, and invoicing and collections. Therefore, it can help create more economic opportunities, increase economic activities, and generates economic growth. Moreover, Fintech reduces information asymmetry in the marketplace and thereby contributing to mitigate risk, which is essential to the stable development of financial activities. It also helps bring additional liquidity to the market and promote the more efficient allocation of scarce resources.

There is the number of studies has found that Information and Communication Technology (ICT) development is an engine of growth since it helps reduce the cost for users, omnipresent in most
business sectors ([1], [2] and [3]). Additionally, Das, Chowdhury, and Seaborn [4] and Andrianaivo and Kpodar [5] suggested that these impacts apply well in developing countries. ICT also made a better financial system which led to economic growth faster since it relaxed the financing constraints that obstructed firm and industrial expansion, and also improved the financial stability ([6], [7] and [8]). Furthermore, financial development encourages the income of the most deprived quintile and hence reduce income inequality ([9] and [10]).

Although the potential of Fintech has drawn the attention of many investors and policymakers around the globe, there are few pieces of research on the economic impacts of Fintech due to the limited Fintech data. To fulfill the literature of these issues, we apply the Fintech data which is available in 2015. The quantile regression (QR) with generalized entropy is employed to handle the small sample sizes.

The generalized maximum entropy (GME) idea is inferring the probability distribution that maximizes information entropy given a set of various constraints. GME approach is robust to multicollinearity problem and misspecification of the error distribution. Besides, many studies have found that GME estimator performs better than several classical estimators such as least squares, maximum likelihood and Bayesian when the extreme quintile is considered ([11] and [12]). Since the adoption of Fintech services and the boom in Fintech startup have grown significantly in most the countries around the world, this study aims to investigate whether Fintech e-payment affects economic development in APEC countries. We employ a generalized entropy QR which allow us to consider the impact in a different group of economy.

The next section provides methodology. Section 3 describes data collection and model estimation. Section 4 presents our empirical results and implementations. The final section concludes.

2. Methodology

2.1. Quantile regression (QR) model
Koenker [13] proposed that quantile regression is desired if conditional quantile functions are of interest. To explain the principles of quantile regression, consider the following model:

\[ y_j = x_{ij}' \beta_j + \epsilon_j \quad ; i = 1, \ldots, k, \text{ and } j = 1, \ldots, n \]  

(1)

where \( x_{ij} \) is \( n \times k \) independent variable, \( \beta_j \) is \( 1 \times k \) vector of coefficients and \( \epsilon_j \) is the error which does not assume any distribution. The QR estimation for \( \beta_j \) proceeds by maximizing the likelihood based on the asymmetric Laplace density (ALD).

There are few studies on QR from an entropy-based perspective such as Bera, GalvaoJr, A. F., Montes-Rojas, G. V., and Park [14] which defined the information entropy of the distribution of probabilities \( p = \{ p_k \}_{k=1}^K \) as an ALD and maximizing entropy measure subject to two moment constraints:

\[ f_{ME}(y) = \arg \max_f \int f(y) \ln f(y) dy \]  

(2)

subject to

\[ E|y - x \beta| = c_1, \]
\[ E(y - x \beta) = c_2, \]

where \( \int f(y) dy = 1; \) \( c_1 \) and \( c_2 \) are known constants.
Although the entropy estimation has already been proposed, it still adheres to the strong ALD assumption on the entropy measures. Thus, another main contribution of this study is to develop an entropy estimation for quantile regression model without assuming the ALD.

2.2. Generalized maximum entropy (GME) estimation

The maximum entropy concept consists of inferring the probability distribution that maximizes information entropy given a set of various constraints. Let $p_k$ be a proper probability mass function on a finite set $A$ where $A=\{a_1, ..., a_K\}$. Shannon [15] developed his information criteria and proposed a classical entropy, that is

$$H(p) = -\sum_{k=1}^{K} p_k \log p_k,$$

where $\sum_{k=1}^{K} p_k = 1$. The entropy measures the uncertainty of a distribution and reaches a maximum when $p_k$ is uniform distribution Wu [16].

This entropy concept is applied in the present model by generalizing the maximum entropy as the inverse problem in the QR framework. Rather than searching for the point estimates $i\tau\beta$, one can view these unknown parameters as expectations of random variables with $M$ support value for each estimated parameter value $(k)$, $Z=[z_1, ..., z_K]$ where $z_k=[z_{k1}, ..., z_{km}]$ for all $k=1, ..., K$. Note that $z$ and $\bar{z}$ denote the lower bound and upper bound, respectively, of each support $z_k$. Thus parameter $i\tau\beta$ can be expressed as

$$\beta^* = \rho \begin{bmatrix} z_{11} & \cdots & 0 & \cdots & 0 & \cdots & z_{1m} \\ z_{21} & \ddots & 0 & \cdots & 0 & \cdots & z_{2m} \\ \vdots & \ddots & \ddots & \ddots & \vdots & \ddots & \vdots \\ \vdots & \ddots & 0 & \cdots & 0 & \cdots & 0 \\ z_{k1} & \cdots & 0 & \cdots & 0 & \cdots & z_{km} \end{bmatrix} \begin{bmatrix} p_{k1} & \cdots & 0 & \cdots & 0 & \cdots & p_{km} \\ p_{21} & \ddots & 0 & \cdots & 0 & \cdots & p_{2m} \\ \vdots & \ddots & \ddots & \ddots & \vdots & \ddots & \vdots \\ \vdots & \ddots & 0 & \cdots & 0 & \cdots & 0 \\ p_{k1} & \cdots & 0 & \cdots & 0 & \cdots & p_{km} \end{bmatrix},$$

$$\beta_k = \rho \sum_{m} p_{km} z_{km}, \quad (5)$$

where $p_{km}$ are the $M$-dimensional estimated probability distribution defined on the set $z_{km}$. Next, similar to the above expression, $\varepsilon_j$ is also constructed as the mean value of some random variable $v$. each $\varepsilon_j$ is assumed to be a random vector with finite and discrete random variable with $M$ support value, $v_j=[v_{j1}, ..., v_{jM}]$. Let $w_j$ be an $M$-dimension proper probability weights defined on the set $v_j$ such that
Using the reparameterized unknowns $\beta^k_\tau$, $\gamma_k$, and $\varepsilon_j$, one can rewrite equation as

$$Y_j = \rho \sum_m p_{1m} z_{1m}(x'_{1,j}) + \ldots + \rho \sum_m p_{Km} z_{Km}(x'_{K,j}) + \rho \sum w_{jm} v_{jm},$$

where the vector $z_{km}^-$ $z_{km}^+$ $q_{km}$ and $v_{jm}$ are convex set that is symmetric around zero with $2 \leq M < \infty$. And

$$\rho_\tau(L) = L(\tau - I(L < 0))$$

is the check function; this gives the $\tau^{th}$ sample quantile with its solution.

Then, the GME estimator for this model can be constructed as

$$H(p, w) = \arg\max_{p, w} \{H(p) + H(w)\} \equiv -\sum_k \sum_m p_{km} \log p_{km} - \sum_j \sum w_{jm} \log w_{jm}$$

subject to

$$Y_j = \rho \sum_m p_{1m} z_{1m}(x'_{1,j}) + \ldots + \rho \sum_m p_{Km} z_{Km}(x'_{K,j}) + \rho \sum w_{jm} v_{jm},$$

$$\sum_k p_{km} = 1, \sum w_{jm} = 1,$$

where $p$, and $w$ are on the interval $[0,1]$.

Consider regressor ($k = 1$), this optimization problem can be solved using the Lagrangian method which takes the form of

$$L = H(p, w) + \lambda'_p(Y_j - \rho \sum_m p_{1m} z_{1m}(x'_{1,j}) - \rho \sum w_{1m} v_{1m}) + \lambda'_w(1 - \sum_m p_{1m} + b'(1 - \sum w_{jm}),$$

where $\lambda'_p$, $\lambda'_w$ and $b'$ are the vectors of Lagrangian multipliers. Thus, the resulting first-order conditions are

$$\frac{\partial L}{p_{1m}} = -\log(p_{1m}) - \sum_m \lambda_{1m}^p \rho z_{1m}(x'_{1,j}) - \rho a_j = 0,$$

$$\frac{\partial L}{w_{jm}} = -\log(w_{jm}) - \sum_m \lambda_{1m}^w v_{jm} - b_j = 0,$$

$$\frac{\partial L}{\lambda}_i = \left(Y_j - \rho \sum_m p_{1m} z_{1m}(x'_{1,j}) - \rho \sum m w_{jm} v_{jm}\right) = 0.$$
Thus, we have

\[ p_{1m} = \exp(-a - \sum_{m} \rho_{r,1m} z_{1m}(x'_{1,j})) = 1, \]  

\[ w_{jm} = \exp(-b - \sum_{m} \rho_{r,1m} v_{jm}) = 1. \]

Then, by setting \( \lambda = 0 \), solving the first order conditions yields

\[ \hat{p}_{1m} = \exp(-z_{1m} \sum_{m} \rho_{r,1m} x'_{1,j}) \]

\[ \sum_{m} \exp(-z_{1m} \sum_{m} \rho_{r,1m}(x'_{1,j})), \]

\[ \hat{w}_{jm} = \exp(-\hat{\lambda}_{1j} \rho_{r} v_{1m}) \]

\[ \sum_{m} \exp(-\hat{\lambda}_{1j} \rho_{r} v_{1m}). \]

3. Data and model estimation

This paper introduces a Fintech e-payment index developed by RMIT University and TRPC (2015). This index gauges the readiness and capacity of each economy to engage in e-payment, the level of use of e-payment and m-payment services, as well as their development potential based on each economy’s e-payment ecosystem. The Fintech e-payment index is constructed by calculating the weighted average of 4 sub-indexes: 1) Regulation and Policy, represents business climate and openness to technology 2) Infrastructure, represents a level of enabling technology and financial connectivity 3) Demand, represents e-payment usage level and latent demand and 4) Innovative Products and Services, represents the supply-side landscape and capacity to innovate, by using 44 indicators related to business, technology, financial access and payments-specific. Therefore, these four sub-indexes represent the e-payment ecosystem.

For the economic development variables, we consider economic growth (GDP), labor productivity (LP), price volatility (PV) and income inequality (GINI). We collect cross-sectional data in year 2016 from 21 APEC economies. The datasets were collected from the International Telecommunication Union, United Nations, World Bank, World Economic Forum, World Intellectual Property Organization, Consumer Barometer, and WeAreSocial.com. Since we consider the role of Fintech e-payment on APEC economic development, in particular, economic growth, income inequality, labor productivity, and price volatility by using a generalized entropy QR. We, in addition, examine the impact of e-payment ecosystem, namely, regulation and policy, infrastructure, demand, and innovative products on those economic development indicators. Our variables used and model estimations are as follows:

\[ \ln y_j = \alpha_i + \beta_i \ln f_{tj} + \varepsilon_j, \]  

where \( \ln y_j \) denotes natural log of economic development variables in country j and \( \ln f_{tj} \) is natural log of Fintech e-payment index including its sub-indexes in country j. \( \tau \) represents conditional quantile of dependent variables given its covariates. Here, we consider quantile level at 0.25, 0.50, and
0.75. For e-payment ecosystem, we decompose $\ln f_t$ into four variables representing each ecosystem, namely regulation and policy ($\ln reg_t$), infrastructure ($\ln inf_t$), demand ($\ln dm_t$), and innovative products ($\ln in_t$), to consider the impact of each component.

4. Empirical results

The parameters estimated at $\tau$ equal 0.25, 0.50, and 0.75 indicating low, medium, and high level of economic development variables, respectively, are presented in Table 1. The empirical results show that Fintech improves economic development especially at $\tau = 0.25$ which provides higher effects compared with those effects at the $\tau = 0.50$ and 0.75. This means that the impact of Fintech is stronger at low level of economic growth. In other words, Fintech provides greater benefits during low level of those economic variables since it fosters economic growth at the low level, improve low labor productivity, and reduce both price volatility and income inequality at the low level.

Furthermore, the results show that Fintech is most important in determining economic growth followed by labor productivity, price volatility, and income inequality, respectively. Interestingly, the demand ecosystem, which represents e-payment usage level and latent demand, makes a significant contribution to economic development, particularly, economic growth.

| Parameter | GDP | LP | PV | GINI | GDP | LP | PV | GINI | GDP | LP | PV | GINI |
|-----------|-----|----|----|------|-----|----|----|------|-----|----|----|------|
| constant  | 0.060 | 0.642 | 0.686 | 1.216 | 0.071 | 0.928 | 0.508 | 1.069 | 0.229 | 0.958 | 0.395 | 0.964 |
| ft        | (0.129) | (0.168) | (0.129) | (0.113) | (0.164) | (0.165) | (0.137) | (0.126) | (0.196) | (0.207) | (0.110) | (0.103) |
| ft        | (0.995) | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.001] | [0.000] | [0.507] | [0.000] | [0.001] | [0.000] |
| ft        | (1.621) | 1.109 | -0.335 | -0.291 | 1.617 | 0.843 | -0.122 | -0.112 | 1.477 | 0.829 | 0.020 | 0.019 |
| ft        | (0.139) | (0.167) | (0.138) | (0.121) | (0.162) | (0.166) | (0.150) | (0.137) | (0.201) | (0.228) | (0.119) | (0.112) |
| ft        | [0.000] | [0.000] | [0.053] | [0.057] | [0.000] | [0.000] | [0.718] | [0.714] | [0.000] | [0.001] | [0.986] | [0.985] |
| inf       | 0.280 | 0.816 | 0.651 | 1.191 | 0.125 | 0.710 | 0.506 | 1.066 | 0.211 | 1.121 | 0.309 | 0.885 |
| inf       | (0.113) | (0.118) | (0.125) | (0.070) | (0.149) | (0.162) | (0.172) | (0.157) | (0.109) | (0.180) | (0.094) | (0.089) |
| inf       | [0.047] | [0.000] | [0.000] | [0.705] | [0.000] | [0.013] | [0.000] | [0.153] | [0.000] | [0.004] | [0.000] |
| inf       | (0.016) | (0.103) | (0.155) | (0.077) | (0.175) | (0.158) | (0.197) | (0.178) | (0.082) | (0.115) | (0.128) | (0.123) |
| inf       | [0.994] | [0.028] | [0.473] | [0.092] | [0.132] | [0.064] | [0.945] | [0.034] | [0.439] | [0.140] | [0.161] |
| ft        | -0.173 | 1.011 | 0.317 | 0.275 | 0.425 | 1.012 | 0.308 | 0.276 | 0.707 | -0.200 | 0.168 | 0.152 |
| ft        | (0.161) | (0.430) | (0.458) | (0.101) | (0.327) | (0.511) | (0.387) | (0.354) | (0.248) | (0.587) | (0.259) | (0.242) |
| ft        | [0.561] | [0.063] | [0.786] | [0.024] | [0.430] | [0.141] | [0.729] | [0.236] | [0.037] | [0.943] | [0.809] | [0.820] |
| dm        | 1.200 | -0.118 | -0.237 | -0.202 | 0.750 | -0.270 | 0.029 | 0.026 | 0.953 | -0.836 | -0.436 | -0.404 |
| dm        | (0.416) | (0.272) | (0.530) | (0.053) | (0.215) | (0.395) | (0.406) | (0.370) | (0.189) | (0.410) | (0.235) | (0.219) |
| dm        | [0.015] | [0.909] | [0.904] | [0.000] | [0.002] | [0.792] | [0.997] | [0.997] | [0.000] | [0.114] | [0.179] | [0.181] |
| dm        | 0.422 | -0.246 | -0.593 | -0.526 | 0.054 | -0.079 | -0.530 | -0.478 | -0.360 | -0.109 | 0.101 | 0.096 |
| dm        | (0.364) | (0.117) | (0.310) | (0.154) | (0.434) | (0.347) | (0.501) | (0.459) | (0.148) | (0.210) | (0.343) | (0.323) |
| dm        | [0.510] | [0.109] | [0.162] | [0.002] | [0.992] | [0.973] | [0.571] | [0.581] | [0.052] | [0.872] | [0.957] | [0.956] |

Note: Values inside the parentheses are standard errors. Values inside the brackets are minimum Bayes’ factor.

At $\tau = 0.25$, referring to the low level of economic variables, Fintech adoption encourages income growth and labor productivity. It also reduces price volatility and income inequality. Based on the minimum Bayes’ factor values, there are decisive evidences that Fintech highly affects growth and labor productivity by 1.621 and 1.109 percentage, respectively. These impacts are greater than the impacts contribute during medium and high level of economic variables. Moreover, it also suggests that e-payment usage level and latent demand (dm) significantly plays an important role to support growth since e-payment usage encourage people consumptions and hence boost economic activities. There is decisive evidence that it also helps reduce income inequality. Furthermore, there is a strong evidence that infrastructure (inf) and the openness to technology (reg) increase labor productivity through technological advancement. The higher level of enabling technology helps improve production efficiency and thus increase productivity. Additionally, innovation (in) has a major contribution on promote equality of income distribution and lower price volatility since they support market competition and reduce the market power of firms.
At \( \tau = 0.50 \) and 0.75, the impact of Fintech on economic growth and productivity diminish during the medium and high level of economic variables. Moreover, unlike during the low level of economic variables, the results present weak evidence that Fintech affects price volatility and income inequality. For the impact of each e-payment ecosystems, during the medium level of economic variables, there is strong evidence that only demand encourages economic growth while the regulation and policy increase labor productivity according to minimum Bayes’ factor. Innovation and infrastructure found only weak evidence that they contribute to economic development during this stage. Additionally, during the high level of economic variables, there are strong evidence that e-payment ecosystems affect only economic based on minimum Bayes’ factor. Demand still has a highest impact on economic growth followed by infrastructure and regulation and policy, respectively. However, the results show that demand also helps encourage productivity, lower price volatility, and narrow income gap but there is only weak evidence according to the minimum Bayes’ factor.

In summary, we found that Fintech obviously promote economic growth and labor productivity. Moreover, Fintech adoption mostly contributes to economic growth through e-payment usage level and latent demand.

5. Conclusions

The objective of this paper is to examine the impact of Fintech e-payment on various indicators of APEC economic development. For Fintech e-payment, we apply the index constructed by RMIT University and TRPC which is comprised of 4 e-payment ecosystems, that is, Regulation and Policy, Infrastructure, Demand, and Innovation. Since the data has a limitation of small sample sizes, we deal with this problem by using QR with GME estimation. We estimate both the effect of overall Fintech e-payment and its ecosystems to see whether they contribute to the improvement of economic development. In our study, we consider quantile level at 0.25, 0.50, and 0.75, corresponding low, medium, and high level of economic variables, respectively.

The empirical estimations present that Fintech plays an important role in APEC economic development. It encourages income growth and productivity as well as lessen price volatility and income inequality. Moreover, we found that the contributions of Fintech on economic development are high during the low level of economic variables but diminish during medium and high level of economic variables. The Fintech adoption has the most impact on economic growth, productivity, price volatility, and income inequality, respectively. In addition, e-payment usage level and latent demand are remarkably gainful to all economic development indicators compare with other e-payment ecosystems. Finally, business climate and openness to technology strongly contribute to increasing GDP growth and productivity.

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References

[1] Tcheng H, Huet J M, Viennois I and Romdhane M 2007 Telecoms and development in Africa: the chicken or the egg *Convergence Letter* **8**(16)

[2] Waverman L, Mesch M and Fuss M 2005 The impact of telecoms on economic growth in developing countries *Vodafone policy paper series* **2** 10–24

[3] Ghosh S 2016 Political transition and bank performance: how important was the Arab Spring? *Journal of Comparative Economics* **44**(2) 372-382

[4] Das A, Chowdhury M and Seaborn S 2018 ICT diffusion, financial development and economic growth: new evidence from low and lower middle-income countries *Journal of the Knowledge Economy* **9**(3) 928-947

[5] Andrianaivo M and Kpodar K 2012 Mobile phones, financial inclusion, and growth *Review of Economics and Institutions* **3**(2) 30
[6] Mehrotra A and Yetman J 2015 Financial inclusion-issues for central banks
[7] Levine R 2005 Finance and growth: theory and evidence Handbook of economic growth 1 865-934
[8] Demirguc-Kunt A and Levine R 2008 Finance, financial sector policies, and long-run growth. The World Bank
[9] Beck T, Demirgüç-Kunt A and Levine R 2007 Finance, inequality and the poor Journal of economic growth 12(1) 27-49
[10] Beck T, Demirgüç-Kunt A and Honohan P 2009 Access to financial services: Measurement, impact, and policies The World Bank Research Observer 24(1) 119-145
[11] Yamaka W, Autchariyapanitkul K, Meneejuk P and Sriboonchitta S 2017 Capital Asset Pricing Model Through Quantile Regression: An Entropy Approach Thai Journal of Mathematics 53-65
[12] Leurcharusmee S, Sirisrisakulchai J, Kingnetr N and Sriboonchitta S 2017 Child-Gender Preference Generalized Maximum Entropy Approach Thai Journal of Mathematics 229-242
[13] Koenker R 2005 Quantile regression Econometric Society Monographs volume 38
[14] Bera A K, Galvao Jr A F, Montes-Rojas G V and Park S Y 2014 Which quantile is the most informative? Maximum likelihood, maximum entropy and quantile regression In Econometric Methods and Their Applications in Finance, Macro and Related Fields pp. 167-199
[15] Shannon C E 1948 A note on the concept of entropy Bell System Tech. J 27(3) 379-423
[16] Wu X 2009 A weighted generalized maximum entropy estimator with a data-driven weight Entropy 11(4) 917-930