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Competition in the Bill Payment Market

Abraham Akra* and Maxwell Stevenson**

This paper models the demand for merchant acceptance and consumer usage of a four- party payment scheme in the bill payment market. Within a cointegrating framework, demand equations are estimated using vector error correction models using proprietary data between March 2003 and December 2010. Results illustrate the importance of network effects in determining consumer usage and merchant demand. Additionally, price elasticities suggest the market for payments in Australia is competitive.

JEL Codes: C32, D12, G20, L14, L80

1. Introduction

The key drivers of transactions in the bill payment market are yet to be defined. The literature concerning the market for payments is largely theoretical, examining the two-sided nature of the payments market. The focus is on the interchange fee set by the payment platform. A two-sided market is characterized as a platform providing goods and services to two distinct end-users with prices set for each type of end-user. Examples of a two-sided market include video game platforms that match game developers and consumers dating agencies that match partners and shopping malls that house a variety of stores. The bill payment market is a two-sided market.

The motivation of this paper is to empirically test for the presence of network effects in the market for payments. Network effects refer to the fact that the value of a particular platform to an end-user increases as the number of end-users on the other side of a transaction increases. The literature emphasizes the importance of network effects to the number of transactions placed over a platform. There has been marginal progress in establishing empirically the role network effects have on transactions in the payments market and this paper is the first to quantify network effects in the market for bill payments. The key limitation in extending the literature empirically is the unavailability of proprietary data. This is reflected in the lack of empirical studies on network effects in the literature.

The data to be used in this study will be provided by BPAY and the Reserve Bank of Australia. BPAY is a dominant platform within the bill payment market accounting for approximately 30% of all transactions. Multivariate Error Correction Models are used to determine whether the network effects hold via a cointegrating framework. Section 2 reviews relevant literature and provides a description of the business model of BPAY, section 3 describes the model and methodology employed, results are provided and section 4 followed lastly by the conclusion in section 5.

*Corresponding author. Discipline of Finance, University of Sydney, Australia .Email :aakr7043@uni.sydney.edu.au
**Dr. Maxwell Stevenson, University of Sydney, Australia. Email:maxwell.stevenson@sydney.edu.au

2. Literature Review

The attention that the market for payments has received from the Reserve Bank of Australia (RBA) has brought about a need for greater understanding of the dynamics of the industry. Interchange fees have been the concern of central banks and antitrust lawsuits throughout the globe. In the recent past in the United States of America, merchants and trade associations filed approximately fifty civil lawsuits against Visa, MasterCard, and several card-issuing banks alleging, among other charges, that interchange fees are too high and that the collective setting of interchange fees by members of the payment card associations constitutes illegal price fixing under antitrust laws. In Australia, the RBA introduced a number of reforms associated with credit and debit card arrangements that sought to moderate, in its opinion, the excessive use of credit and debit cards. This introduction was aimed at increasing the efficiency of the payments system.

As previously noted, the literature exploring the market for payments is largely theoretical. Of central importance to two-sided markets are usage and membership (network) externalities. Usage externalities arise because each party in a given transaction evaluates their own costs and benefits associated with a particular payment method, but do not consider the costs and benefits of the other end-user. Network externality refers to the fact that the value of a particular platform to an end-user increases as the number of end-users on the other side of a transaction increases. For example, in relation to the payments market, the more merchants that offer a particular payment instrument, the higher the value that consumers place on being part of that platform. With more consumers joining the platform, the higher the value merchants place in offering the payment method. This results in an increase in the demand of merchants wishing to join the platform.

Until recently, the set of assumptions assigned to models developed in the literature were limited in their applicability and ability to describe the market for payments. Guthrie and Wright (2007) model the interaction between merchants in a Hotelling world within a game theory framework. The assumptions of their model include no annual fee for consumers, no fixed fee for merchants in joining a platform, as well as both sides having the option to join both platforms. The appealing aspect of the model considered by Guthrie and Wright (2007) is the incorporation of the utility of consumers into the benefits that merchants gain by having their preferred payment option. This feature is apparent in retail firms where merchants rarely refuse a payment instrument preferred by their consumers due to the benefits derived from a transaction. Additionally, in a competitive market, refusing a payment option will put the firm at a competitive disadvantage and send negative signals to consumers regarding the merchant's quality. Consequently, the resulting interchange fee is the upper bound of the range of possible interchange fees and, assuming the card association will maximize volume, this will result in an over-usage of cards. With two competing card schemes, the equilibrium interchange fee is dependent upon the initial behaviour of consumers and merchants. Assuming consumers always hold both cards whenever it is an equilibrium for them to do so, competing card schemes set interchange fees at the socially optimum level. If merchants always accept both cards whenever it is equilibrium for them to do so, competing card schemes set interchange fees at the same level as in a single card scheme. Thus, unlike other markets, competition does not drive down prices. This is a unique characteristic of two-sided markets.

In a variant to Guthrie and Wright (2007), Gardner and Stone (2009) model competition between three-party payment schemes. A three-party payments platform consists of a consumer, merchant and platform. The model developed by Gardner and Stone (2009) seeks to replicate the conditions under which consumers and merchants decide to use a payment platform in a competitive market. The key feature of the model developed by Gardner and Stone (2009) relates to the average cost per transaction of the consumer being inversely related to the quantity of transactions placed on the respective platform. The assumption that consumers pay a fixed cost to join a platform and pay no fees per transaction, allows this parameter to vary between consumers. This is in contrast to Guthrie and Wright (2007) where consumers pay no joining fee but are charged per-transaction. The second crucial assumption lacking in prior literature is common in both Guthrie and Wright (2007) and Gardner and Stone (2009). That assumption relates to the ability of consumers and merchants to subscribe to both platforms.

Gardner and Stone (2009) numerically simulate their model to determine the pricing strategies of platforms for different assumptions relating to operating costs of the platform. The operating platform costs involved in this simplified model are the cost to process a transaction and the fixed cost associated with registering a consumer or merchant. The results suggest merchants are trying to steer consumers to their preferred payment method by only accepting one platform to carry out transactions. The allocation of the total cost directed to the two-sides of the market has long been argued in the literature to favour the side that joins one platform (single-home). The intuition behind this theory suggests platforms price competitively to the single-homing side to attract them to the platform. In doing so, increasing the network externalities as the scale of the network grows. This result, that the single-homing side attracts a lower cost allocation in relation to the multi-homing side, is based on models that were developed with the assumption that one side cannot multi-home and costs do not vary with transactions on the platform. The simulation results provide evidence to the contrary. The multi-homing side pays less as a proportion of total fees charged than the side that is more likely to single-home. Gardner and Stone (2009) attribute this result to average transaction costs varying between consumers and allowing both sides to multi-home.

Empirical studies in the payments market to date have been limited. Restrictive access to propriety data has confined studies to collecting data from surveys and investigating the factors that influence decisions made at checkouts by consumers. In overcoming the restrictive data problem, Rysman (2007) employed a rich data set consisting of two parts. The first part consisted of a panel of households that held multiple payment cards from1994 − 2004, while the second part contained the number and amount of transactions by month of every merchant in the Visa network. Rysman (2007) finds consumers maintain cards on multiple networks but tend to use only one network. This result is found to be robust across consumer characteristics such as income, education and spending. There was also evidence found for network effects in the card payments market. Rysman (2007) finds evidence for network effects by estimating consumer usage and merchant acceptance demand equations in isolation. However, network effects suggest endogeneity between merchant acceptance and consumer usage in their respective demand equations, implying the estimated parameters are biased and inconsistent.

Simon et al. (2010) study the impact a reward program and interest free period has on credit card usage. The dataset consisted of a sample of consumers, whose payment details were recorded in a diary over a two week period, along with information relating to the transaction. Simon et al. (2010) follow the methodology of Borzekowski et al. (2008), in which a series of probit models are estimated to study the effects of various factors, including price incentives, on debit card usage. Results indicate income has a large effect on the probability of holding a card. Relative to the base case of income of $40, 000 − $59, 999, there is a statistically significant drop in the likelihood in owning a card for low income individuals. Holding a debit card also plays a role in determining the probability of card ownership. Ownership of a scheme debit card decreases the probability of ownership of a credit card by 13.2%. Income has a significant effect on having a loyalty program attached to card membership. For consumers earning less than $20, 000, the probability of being part of the loyalty program is 32.3% less likely relative to consumers earning between $40, 000 −$59, 999. This result may be due to the high annual fees or interest rates attached to cards with loyalty programs where the consumer needs to reach a particular level of expenditure in order to be compensated.

The majority of the findings in the literature are fairly represented in the theoretical and empirical papers discussed thus far, with a particular focus on credit cards. However, no model has been developed that has empirically tested the demand functions of consumers and merchants in the bill payment market. Rysman (2004) proposes a framework to model demand in a two-sided market that can be applied to the payments market with network effects and incompatible markets. The market for payments satisfies these two conditions.

Rysman (2004) models the demand of merchants to place advertisements in Yellow Pages directories and consumers demand for usage. The Yellow Pages directory is the platform in this two-sided market, with advertisements in the directory (platform) representing the service offered by the platform to merchants. Consumers value the platform in order to contact a suitable merchant. The network effect in the market for Yellow Pages directories concerns consumer usage and advertising.

The Rysman (2004) data set consists of several sources. The data collected to model consumer usage, is obtained from the National Yellow Pages Monitor (NYPM) and consists of the number of consumer references per month in a household in every metropolitan statistical area for the 476 directories in the sample. Advertising is proxied by the number of pages in the directory. The Yellow Pages Publishers Association (YPPA) maintains reserves of directories and the Boston Consulting Group has collected data detailing the number of pages in each directory. Pricing information of advertisements in a directory is obtained by the YPPA, which has prices for advertisements that vary by size and style. Rysman (2004) formulates the model of merchant demand for advertising by deriving the first-order conditions of maximizing profit from advertising in the Yellow Pages directory. The expression for the demand of consumer usage is obtained using the model in Berry (1994). Finally, the first-order condition of maximizing profit for the publisher of the directory is also derived to complete the model. Equilibrium outcomes for different assumptions relating to social welfare are determined by comparing outcomes estimated under competition and concentrating the market to a single directory. The results suggest consumer usage of a directory is positively related to the quantity of advertising in the directory. A merchant will be willing to pay extra as a result of increases in consumer usage. Both these results suggest a positive network effect in the market for Yellow Pages directories. Equilibrium outcomes suggest the benefits of competition improve social welfare in comparison with coordinating the two sides of the market on a single platform (monopoly). Thus, the network effect is not strong enough to compensate consumers and merchants for increased prices.

2.1 Pricing Structure of the Bill Payment Market in Australia

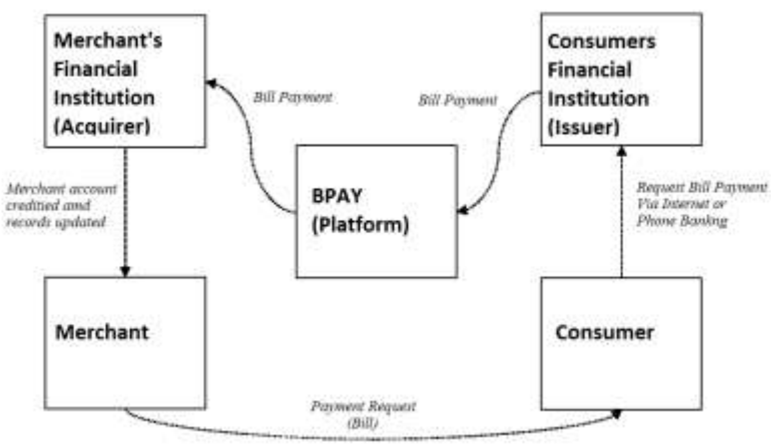
The Australian bill payment market is dominated by BPAY, direct debit, Australia Post and credit card providers. The pricing structure to end-users of these platforms is dependent on whether benefits are provided to consumers by transacting on the platform. BPAY, Direct Debit and Australia Post provide no monetary benefit to consumers that choose their platform to pay a bill. However credit cards, such as those belonging to Visa and Master- Card, provide reward points that can be transformed into shopping vouchers or discounts in future purchases. A platform's decision to not allocate benefits or costs to consumers that use the platform suggests growth in volume can only be achieved by maximizing merchant acceptance.

2.2 Industry Characteristics of BPAY

BPAY is a payments scheme that allows internet and phone bankers to make payments to BPAY billers through their bank. BPAY has been operating for 11 years. The scheme processes these payments and delivers them to the biller's bank for delivery to the biller. BPAY has approximately 30% share of the bill payment market and the volume of transactions continues to grow at over 10% per annum.

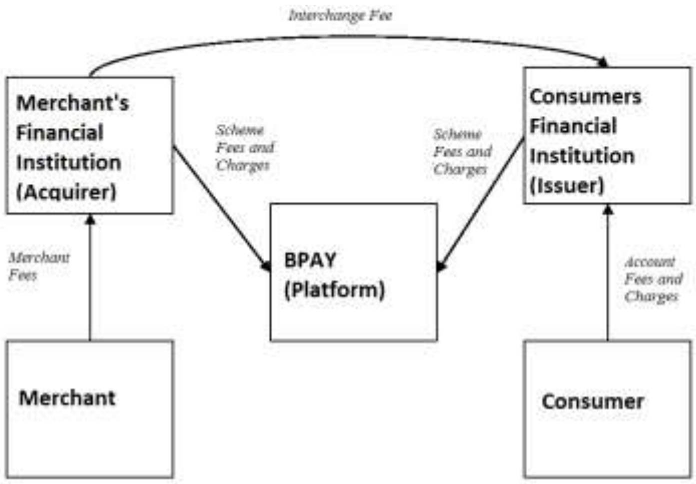
The operating model of BPAY involves a consumer, merchant and their respective banks. As shown in Figure 1, a transaction is initiated by the consumer and the merchant sends a payment request (bill) to the consumer to be made by a given date. The consumer then enters a biller code and a unique customer reference number, along with a payment amount to be debited from a nominated bank account. The payment is then credited into the merchant's bank account via BPAY.

Figure1: Four-Party Payment Process Flow



The structure of the BPAY four-party scheme is similar to that of Visa and MasterCard and is illustrated in figure 2. An interchange fee is paid by the acquirer to the issuer for services performed in transmitting the information to BPAY and there is a separate fee paid to BPAY by the acquirer and issuer per transaction. These fees are set by the platform. The merchant is charged a fee per transaction by their financial institution which is commonly a fixed percentage of the value of the transaction. There are typically no fees charged by banks to consumers.

Figure2: Four-Party Payment Process Flow



3. The Bill Payment Model and Methodology

To determine the key drivers of transactions in the bill payment market, the network effects between consumer usage and merchant acceptance needs to be modelled. The approach of Rysman (2004) will be modified and used to model the interaction between consumers and merchants in order to capture the network effects underlying their respective demand functions.

Within a simplified framework, the role of the issuer (consumer's bank) and acquirer (merchant's bank) will not be modelled. The network effects within the bill payment market can then be described by the following system of equations:

$$U_j^c = a\left(CV_j\right), \quad (1)$$

$$R_j = b\left(U_j^c, P_j^m, \hat{P}_k^m\right), \quad (2)$$

$$CV_j = c\left(R_j, P_j^c, \hat{P}_k^c\right), \quad (3)$$

where: CV_j = Consumer value for platform j.
U_j^c = Consumer usage of platform j.
R_j = Retailer acceptance of platform j.
P_j^m = Merchant fees for accepting platform j.
$\hat{P}_k^m$ = Merchant fees for accepting platform k.
P_j^c = Consumer benefits of transacting over platform j.
$\hat{P}_k^c$ = Consumer benefits of transacting over platform k.

Equation (1) describes the number of transactions placed over platform j as a function of the value a consumer places on that platform. The value placed on a platform may be dependent upon the ease of use, probability of fraud, benefits provided to the consumer via the platform and merchant acceptance. However, from the perspective of modelling the network effects between consumer usage and merchant acceptance, the primary variable of interest is consumer value. The impact of the network effect is captured in equation (2), with merchant acceptance being a function of consumer usage. Lastly, equation (3) completes the network effect between consumers and merchants.

The three first-order conditions consistent with network effects in the bill payment market are as follows:

$$\frac{\partial U_j^c}{\partial CV_j} > 0, \tag{4}$$

$$\frac{\partial R_j}{\partial U_j^c} > 0, \tag{5}$$

$$\frac{\partial CV_j}{\partial R_j} > 0 \tag{6}$$

These first-order conditions detail the network effects within the bill payment market and complete the network between merchant acceptance and consumer usage. All three equations describe a-priori expectations in modelling the demand functions of consumers and merchants. Equation (4) expresses the positive relationship between consumer value and consumer usage, while equation (5) dictates how merchant acceptance increases with consumer usage. Similarly, equation (6) details how the consumer value placed on a platform increases with retailer acceptance. The work of Rysman (2004) finds that equation (4) and (6) are sufficient for identification of network effects.

Estimating equations (1) to (3) is problematic as consumer value is difficult to estimate empirically. While it is hypothesised some of the factors that influence include merchant acceptance, time using the platform, wealth, occupation, access to alternative platforms, fees and rewards, such a data set would be time consuming and difficult to obtain. However, lack of access to this data should not hinder modelling network effects. Accordingly, consumer usage will be used as a proxy for consumer value. In the above framework, this amounts to estimating the following equations:

$$U_j^c = a\left(c\left(R_j, P_j^c, \hat{P}_k^c\right)\right), \tag{7}$$

$$R_j = b\left(U_j^c, P_j^m, \hat{P}_k^m\right), \tag{8}$$

Network effects are thereby identifiable from expressions (7) and (8). Therefore, the modified first-order conditions that are consistent with network effects in the bill payment market are as follows:

$$\frac{\partial U_j^c}{\partial R_j} > 0, \tag{9}$$

$$\frac{\partial R_j}{\partial U_j^c} > 0, \tag{10}$$

3.1 Models of Consumer Usage and Merchant Acceptance

Estimation of equations (7) and (8) is of central importance in testing for network effects. In empirical macroeconomics, the Cobb-Douglas production function is used to govern the functional form of a set of outputs to inputs. Network effects within the bill payment market consider the total usage of both end-users. This macroeconomic perspective of the bill payment market provides an opportunity to model equation (7) and (8) using Cobb- Douglas functions.

$$V\left(M, P_c, \hat{P}_c, \tilde{P}_c, X\right) = aM^{\alpha} P_c^{\tau} \hat{P}_c^{\vartheta} \tilde{P}_c^{\pi} X^{\gamma} \tag{11}$$

$$M\left(V, P_m, \hat{P}_m, \tilde{P}_m\right) = bV^{\beta} P_m^{\delta} \hat{P}_m^{\lambda} \tilde{P}_m^{\phi} \tag{12}$$

where: V = Volume of transactions.

M = Number of Merchants offering the BPAY platform.

X = Matrix of dummy variables.

P_c = Usage fees or benefits of the BPAY platform.

$\hat{P}_c$ = Usage benefits of transacting on the Visa platform.

$\tilde{P}_c$ = Usage benefits of transacting on the Diners Club platform.

P_m = Merchant fees of the BPAY platform.

$\hat{P}_m$ = Merchant fees of the Visa platform.

$\tilde{P}_m$ =Merchant fees of the Diners Club platform.

Equation (11) and (12) form the basis of estimation by applying the Cobb-Douglas production function to the bill payment market. Taking logarithms of equation (11) and (12) has the attractive property of transforming parameters into elasticities. The parameters of interest in this paper are α and β, where a statistically significant value supports the existence of a network effect in the bill payment market. Taking logarithms, enables the parameters of equation (11) and (12) to be linear. This transforms equation (11) and (12), as provided below:

$$v\left(m,p_c,\hat{p}_c,\tilde{p}_c,x\right) = \bar{a} + \alpha m + \tau p_c + \theta\hat{p}_c + \pi\tilde{p}_c + \gamma x \quad (13)$$

$$v\left(m,p_c,\hat{p}_c,\tilde{p}_c,x\right) = \mathring{a} + \alpha m + \theta\hat{p}_c + \pi\tilde{p}_c + \gamma x$$

$$\mathring{a} = \bar{a} + \tau p_c$$

$$m\left(v,p_m,\hat{p}_m,\tilde{p}_m\right) = \bar{b} + \beta v + \delta p_m + \lambda\hat{p}_m + \phi\tilde{p}_m \quad (14)$$

where: $v = \log(V)$

$m = \log(M)$

$p_c = \log(P_c)$

$\hat{p}_c = \log(\hat{P}_c)$

$\tilde{p}_c = \log\left(\tilde{P}_c\right)$

BPAY and the issuer do not charge consumers to transact on BPAY's platform. Therefore, $p_c$will be modelled as a constant with a value close to zero. The resulting model for consumer usage of BPAY is given by expression (13). It is expected that network effects will be present, signified by a statistically significant result for α and β.

Of additional interest is the price elasticity of merchants to costs imposed by the platform. It has been commonly hypothesized in the literature pertaining to the development of theoretical models in the market for payments that $\alpha < \beta$. As the price allocation by the platform in practice has been in the consumers favour, they are less likely to multi-home.

The estimation of merchant and volume elasticities in equation (13) and (14) is obtained within Johansen's maximum likelihood cointegration framework. The vector autoregressive (VAR) model is advocated by Sims (1980) as a way of estimating dynamic autoregressive relationships between endogenous variables without presupposing erogeneity restrictions on some variables.

3.2 Data

The lack of access to proprietary data in the market for payments has been the primary cause of limited empirical studies of network effects. BPAY has made available quarterly data between March 2003 and December 2010 relating to consumer usage, merchant acceptance and interchange fees. Quarterly statistics from the RBA complete the data set. There are two limitations associated with this data set. To understand these shortcomings, prior to outlining the data used to estimate the demand equations of merchants and consumers, it is beneficial to review the structure of the BPAY platform.

To estimate the demand equations of merchants and consumers, the merchant fees and the account fees and charges of consumers that use BPAY are required. However, these costs are not publicly available. It has been observed in practice that there is a high correlation between the interchange fee set by the platform and the merchant fee the acquiring bank sets per transaction. Therefore, the interchange fee for BPAY is used as a proxy for merchant fees for this platform. The RBA publishes quarterly the average merchant fees of Visa/MasterCard and Diners Club, thus no proxy is required for $\hat{p}_m$ and $\tilde{p}_m$ in equation (14).

The second data shortcoming relates to the ability to estimate the benefits of using an alternative platform to BPAY. The literature in the market for payments describes a positive relationship between interchange fees, merchant fees and benefits supplied by the platform or the issuing bank, to the consumer. Effectively, merchants subsidize the cost for consumers to use the platform. The greater the interchange fee, the greater the merchant fee that the acquiring bank charges and therefore, the greater the revenue for the issuing bank. The revenue that is raised by the issuing bank is used to provide benefits to consumers to use the platform. There is no financial benefit or cost in transacting over the BPAY platform. However, there are rewards attached to using a credit card. Data relating to the benefits of using a Visa/MasterCard is only available annually. To increase the number of degrees of freedom in estimation, a proxy is required. The correlation between the average merchant fees and benefits of Visa/MasterCard is 98.5%. Thus, merchant fees will be used as a proxy for benefits in equation (13). The list of the variables that is required to estimate the parameters of interest are quarterly transaction volume, number of active biller codes and average merchant fees of BPAY, Diners Club and Visa/Mastercard expressed as a percentage of a transactions value.

4. Results

4.1 Johansen Maximum Likelihood Procedure

The Johansen cointegration test satisfied all the assumptions relating to the residuals being serially uncorrelated, homoskedastic and normally distributed. The lag length was chosen to maximize the degrees of freedom in estimation. Accordingly, the residuals were subject to a LM test for serial correlation. In the event that the residuals were serially correlated, additional lags were added to the model to solve the problem.

Table1: Johansen Cointegration Tests

Demand	λ_{Max} H_0 :rank=r			$\lambda_{Trace}H_0$:rank=r		
	r=0	r=1	r=2	r=0	r=1	r=2
Consumer	36.1*	18.9	9.6	66.4*	30.2*	11.3
Merchant	39.8*	16.0	14.7	85.5*	45.7	29.6

Table1 contains the Johansen cointegration test results for the respective demand equations. The cointegrating rank is determined by a sequential testing procedure, which initially starts with examining H_o: r = 0. A large test statistic is evidence against the Ho and as- summing it is rejected, $H_{o:}$ r ≤ 1 is evaluated. The process continues until H_o is not rejected and the cointegrating rank attained is the number of cointegrating vectors present in the VAR.

The critical values differ between the consumer usage and merchant acceptance demand equations due to the presence of dummy variables in the demand equation for consumer usage. The critical values for the λ_{Max} and $\lambda_{T\ race}$ test statistics at the 5%

level of significance (los) in testing for cointegration in the consumer usage demand equation are 27.6 and 47.9 for $H_o: r = 0$, 21.1 and 29.8 for $H_o: r \leq 1$ and 14.3 and 15.5 for $H_o: r \leq 2$, respectively. For the merchant acceptance demand equation, critical values for the λ_{Max} and λ_{Trace} test statistics at the 5% level of significance in testing for cointegration are 33.9 and 69.8 for $H_o: r = 0$, 27.6 and 47.9 for $H_o: r \leq 1$ and 21.1 and 29.8 for $H_o: r \leq 2$, respectively. An (∗) represents a rejection of the null hypothesis at the 5% level of significance.

The results indicate there is one cointegrating vector in the consumer usage demand equation based on the maximum eigenvalue (λ_{Max}) test statistic and two cointegrating vectors based on the Trace (λ_{Trace}) test statistic at the 5% los. At the 1% los, both test statistics suggest that there is only one cointegrating vector. As the rejection of the null hypothesis that r = 1 is marginal (p-value = 0.045) based on the λ_{Trace} test statistic at the 5% los, the confidence in rejecting the null hypothesis and the corresponding theory that there is only one cointegrating vector is minimal. The test based on the λ_{Max}does not reject the null hypothesis that r = 1. It does so with high confidence, with the p-value associated with the test statistic of 18.9 being 0.1.

The consequences of establishing cointegration are vital and considering the poor finite sample properties of the Johansen maximum likelihood procedure, a more cautious approach in selecting the loss is required. Therefore, a loss of 1% seems more appropriate, thereby concluding there is one cointegrating vector in the consumer usage demand equation.

Based on the two test statistics, there appears to be a single cointegrating vector in the merchant acceptance demand equation. At the 1% and 5% los, the null hypothesis that r=0 is rejected based on the λ_{Max} and λ_{Trace} test statistics. In comparison, the non-rejection of the null hypothesis that r = 1 at the 1% and 5% los. Therefore, it can be concluded that there is evidence for a single long-run relationship between all variables in the consumer usage and merchant acceptance demand equations of (13) and (14).

4.2 Vector Error Correction Model

4.2.1 Consumer Usage

$$\begin{aligned}
\Delta v_t &= 0.02 + 0.034X_1 - 0.12e_{t-1} - 0.14\Delta v_{t-1} + \qquad (15) \\
&\quad (3.19) \quad (3.83) \quad (-2.15\ ) \quad (-0.89) \\
&\quad 0.34\Delta m_{t-1} + 0.012\Delta\hat{p}_{t-1} + 0.006\Delta\tilde{p}_{t-1} + \varepsilon_t \\
&\quad (1.46) \qquad (0.14) \qquad (0.05) \\
R^2 &= 0.54,\ LM\text{-}Stat = 20.8, F_{H_0:\beta_i=0\ \forall\ i} = 4.58
\end{aligned}$$

The ECM given by equation (15) partially presents the VECM estimated. For the sake of brevity, only the ECM of consumer usage is presented. The estimated model is statistically valid, with errors being serially uncorrelated, normally distributed and the parameters being jointly statistically significant. Autocorrelation was tested up to three lags, by applying a LM test (Breusch–Godfrey test). The p-value associated with the observed test statistic of 20.8 equaled 0.19, thereby not rejecting the null hypothesis of the errors being independent at the 5% loss. The critical F-statistic to test whether the model is empirically valid at the 5% loss is approximately 2.55, the observed F-statistic is 4.58, thereby rejecting the null hypothesis and concluding that the model is empirically valid. In addition, there is no evidence of the errors being heteroskedastic. As the data set consists of multiple time series variables, observing that the errors are homoskedastic is expected. The model fits the data well with 54% of the variation in the growth of volume being explained by the model.

In establishing that the model is empirically valid by observing that the errors follow the classical assumptions of linear regression and testing for the joint significance of the parameters, the parameters can be used to assess the expected impact of various variables on consumer usage. To account for the seasonality in the data, the model initially had three deterministic dummy variables that represent the March, June and September quarters. The base quarter was the December quarter. However, the t-statistics observed for the March and June quarters were 1.6 and 0.27 respectively, which implies at the 5% los that both the March and June quarters are no different to that of the December quarter. Thus, only the September dummy variable was included in the model as it attained an observed t-statistic of 3.83, which implies it is statistically significant at the 5% los with a p-value of approximately zero. Therefore, on average, in the September quarter the volume of transactions is 3.4% greater than that of other quarters, holding all other factors constant.

The parameters of the variables that are expressed as rates of change provide the short-run impacts on consumer usage. A one percent increase in merchant acceptance is expected to increase volume by 0.34%, other things being held constant. Whereas a 1% increase in the benefits of transacting on the Visa or Diners Club platform is expected to increase volume by 0.012% and 0.006% respectively, other factors being held constant. The impact on volume from an increase in the benefits of an alternative platform is expected to be negative. However, as the magnitude of the increase in volume is small, it can be argued in the short-run there is no impact on volume from a change in the benefits of alternative platforms as consumers take time to adjust billing payment habits and become members of the respective credit card platforms.

$$\begin{aligned} v_t &= 14.9 + 0.55m_t - 1.07\hat{p}_t - 0.75\bar{p}_t \qquad (16) \\ \alpha &= 0.12 \end{aligned}$$

The long-run relationship between consumer usage, merchant acceptance and the benefits of transacting on the Visa and Diners Club platform is given by equation (16). All prior conditions regarding the signs of the parameters are satisfied. The first condition of network effects in the bill payments market is met with the parameter of merchant acceptance being positive. More specifically, a one percent increase in the merchant acceptance of BPAY is expected to increase consumer usage by 0.55% in the long run. As expected, the impact of alternative platforms to BPAY increasing the benefits to consumers has a negative effect on volume. A one percent increase in the benefits to the usage of the Visa and Diners Club platform is expected to decrease consumer usage on the BPAY platform by 1.07% and 0.75% respectively, other things being held constant. The adjustment coefficient is quite low at 0.12, meaning

12% of the disequilibrium error is made up in the following period. Hence, consumer usage does not adjust quickly back to equilibrium following deviations from the equilibrium relationship.

The results indicate that the growth of the BPAY platform has been driven by the actions of competing platforms. The magnitude of the parameter associated with Visa is almost twice that of merchant acceptance. The downward trend in interchange fees, and thereby the fall in benefits to consumers, has had a positive effect on the volume of transactions placed with BPAY. The market for bill payments appears competitive, with consumers being price sensitive to other platforms in the bill payment market, as reflected by the magnitude of the cross-price elasticities of Visa and Diners Club.

4.2.2 Merchant Acceptance

$$\begin{aligned}
\Delta m_t &= \underset{(3.2)}{0.02} - \underset{(-5.7)}{0.41 e_{t-1}} - \underset{(-1.03)}{0.16 \Delta m_{t-1}} - \underset{(-0.25)}{0.03 \Delta v_{t-1}} - \underset{(-0.64)}{0.53 \Delta p_{t-1}} - \qquad (17)\\
&\quad \underset{(-2.8)}{0.18 \Delta \hat{p}_{t-1}} - \underset{(-1.34)}{0.12 \Delta \bar{p}_{t-1}} + \varepsilon_t \\
R^2 &= 0.65,\ LM\text{-}Stat = 17, F_{H_0:\beta_i=0\,\forall\, i} = 6.4
\end{aligned}$$

Equation (17) is another part of a system of equations estimated via a VECM. There is no evidence of autocorrelation and the model as a whole is valid, with the null hypothesis associated with $\beta_i = 0\ \forall i$ being rejected at the 5% los. Autocorrelation was tested up to two lags, by applying a LM test. The p-value associated with the observed test statistic of 17 equaled 0.84, implying the errors are not serially correlated. The critical F-statistic to test whether the model is empirically valid at the 5% loss is 2.55, the observed F-statistic given by equation (17) is 6.4, and hence the model is empirically valid. The data fits the model well with 65% of the variation in the growth of merchant acceptance being explained by the model.

The short-run changes in merchant acceptance are all negative to changes in volume and the merchant fees of BPAY, Visa and Diners Club. A one percent increase in consumer usage is expected to decrease merchant acceptance initially by 0.03%, other things being equal. An increase of one percent in the merchant fee of BPAY is expected to decrease merchant acceptance by 0.53%, other things being constant. Additionally, a one percent increase in the merchant fees of Visa and Diners Club are expected to decrease merchant acceptance by 0.18% and 0.12% respectively, holding all other factors constant.

$$\begin{aligned}
m_t &= -4.69 + 0.75 v_t - 0.27 p_t + 0.53 \hat{p}_t + 0.27 \bar{p}_t \qquad (18)\\
\alpha &= 0.41
\end{aligned}$$

The long-run relationship between merchant acceptance, volume and the merchant fees of all platforms is given by equation (18). In the long-run, a one percent increase in volume is expected to increase merchant acceptance by 0.75%. Hence, as the coefficient of volume is positive, the second condition for the existence of network effects is satisfied in the market for bill payments. Thus, it can be concluded that volume increases with merchant acceptance from equation (16) and merchant acceptance increases with volume, as shown by equation (18). The adjustment coefficient is reasonably high at 41%; hence 41% of the disequilibrium error is made up in the following period. Thus, merchant acceptance adjusts quickly back to equilibrium following deviations from the equilibrium relationship.

A second observation can be made in reference to the magnitude of the network effect parameters, given by equations (16) and (18). Currently, the allocation of costs between end-users in the market for bill payments is weighted towards the merchant. The results given by the two demand functions of consumer usage and merchant acceptance support the decision of payment platforms to have merchants subsidize the cost of consumers using the platform. This is supported by the parameter of volume in equation (18) being greater than the parameter of merchant acceptance in equation (16). Therefore, consumers have a greater influence on merchant acceptance than does merchant acceptance have on consumer usage. Thus, the bill payment platform is directed to entice consumers to use the platform in order to increase merchant acceptance. The platform does so by having merchants subsidize the cost of consumers using the platform. For example, BPAY have no usage and joining fees for consumers to pay their bills, however merchants are required to pay merchant fees and a cost for subscribing to the platform.

It is interesting to observe that the short-run effect of an increase in the merchant fee of BPAY is much greater than the long term effect of such a change. The immediate impact of increasing the merchant fee of BPAY by 1% is an expected decrease of 0.53%, other things being held constant. However the long-term change in merchant acceptance is a decrease of 0.27%. The increase in merchant acceptance after the initial fall from an increase in merchant fees suggests merchants react quickly to changes in the cost of payment instruments. This result may be explained by the expected network effects within the bill payments market and competition between merchants to attract marginal consumers.

Marginal consumers are a segment of a market that views merchants in a selected industry equally and differentiates according to the payment options available. In a competitive market, merchants price goods and services at similar prices that don't vary considerably across merchants. Merchants therefore try to attract consumers by offering their preferred payment method; thereby providing incentives for merchants that didn't offer BPAY to join the platform and capture those marginal consumers. Consequently, the merchant that has withdrawn from the BPAY platform may re-join the platform in order to recapture those marginal consumers.

The cross-price elasticity of demand for merchant acceptance shares similar attributes to that of the price elasticity of BPAY. There is a clear distinction between the short-run and long-run impact on merchant acceptance from a change in merchant fees. The initial effect of an increase in the merchant fees of Visa and Diners Club is a fall of 0.18% and 0.12% in the merchant acceptance of BPAY, respectively. On the other hand, the long-run effect of an increase in the merchant fees of Visa and Diners Club is an increase in the merchant acceptance for the BPAY platform of 0.53% and 0.27%, respectively. The slight fall in demand in the short run may be a response by merchants to decrease the overall costs of payment instruments made available to consumers in the short term. However, merchants that may not have offered BPAY previously will have incentives to do as in the future as the cost of offering the more expensive alternative, Visa and Diners Club, rises. Therefore over the long-run, merchant acceptance will increase. From a competitive perspective, if a merchant in a competitive market does not offer a particular platform that others do, the perceived value of that merchant declines and marginal consumers will purchase elsewhere. Thus, those platforms that initially left the BPAY platform due to the rise in the merchant fees of Visa and Diners Club may re-join the platform.

The price and cross-price elasticities provide a gauge to how competitive the market for bill payments is. The magnitude of the cross-price elasticity of Visa is almost double that of the price elasticity of BPAY. This implies Visa is a dominant platform in the market for bill payments. Merchants in aggregate are therefore more sensitive to changes in pricing from Visa compared to that of BPAY in deciding whether to join the BPAY platform.

5. Conclusion

This paper has developed a model for consumer usage and merchant acceptance to test for the presence of network effects in the bill payment market. Using data from the RBA and proprietary data provided by BPAY between March 2003 and December 2010, Johansen's maximum likelihood procedure was employed to estimate and test for a cointegrating vector in the demand models of consumer usage and merchant acceptance. In comparison to earlier studies, such as that of Rysman (2007), the endogeneity that network effects imply in two- sided markets is accounted for by the vector autoregressive framework. Additionally, this is the first study to estimate price elasticities and cross-price elasticities of a platform in the bill payment market.

The results indicate the existence of a network effect between consumer usage and merchant acceptance in the market for bill payments. Consumers are more valuable to the BPAY platform as their effect on merchants is greater than that of merchant acceptance on consumer usage. There is also a clear distinction between short-run and long-run effects from changes to the variables that define the consumer usage and merchant acceptance demand models. The pricing elasticities indicate the market for bill payments is competitive, with consumers and merchants reacting strongly to changes in benefits and merchant fees. The next logical step is to investigate the drivers of transactions for consumers and merchant acceptance from a microeconomic perspective as the adoption of electronic means of transacting gains popularity through technological advancement.

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