Modelling the Co-dependent Diffusion of Innovation in Two-sided Markets

A thesis presented in partial fulfilment of the

requirements for the degree

of

Doctor of Philosophy in Marketing

at Massey University, Albany Campus, New Zealand

Xing (Alison) Chen
2023

Abstract

With the advancement of technology, many innovations, like Electric Vehicles (EV) and contactless payment, are co-dependent. The diffusion of co-dependent innovation requires joint usage from more than one adopting group to enable functionality. For instance, EV owners will not drive their EVs unless they know that there are charging stations along their trips. Contactless payers will not pay with a "waving" or "tapping" of their contactless-enabled cards at the checkout unless they know that merchants accept this payment method.

Prior literature terms innovations that are compatible and can be used together as complementary innovations, and those adopted in sequence as contingent innovations (Peterson & Mahajan, 1978). Researchers build models of such innovations based on multi-product growth models or the hardware-software paradigm relying on the operation of the network effects (Bayus, 1987; Bucklin & Sengupta, 1993b; Stremersch et al., 2007). However, these terminologies fail to accurately describe co-dependent innovations, which require uptake by more than one adopting group and will only function with simultaneous use. When there are two distinct adopting groups, the market in which the innovation diffuses is a two-sided market. There is co-dependency between the adopting groups, and thus, between the diffusion path of each innovation. As the diffusion of these co-dependent innovations is yet to be modelled, the current study aims to fill this gap.

Using eight years of transaction-based data on a novel payment innovation in a developed western economy, we conceptualise co-dependent diffusion of innovation and examine its properties with three empirical studies. Results from Study 1 (presented in Chapter 2) demonstrate that prior models, including the multi-product Bass model, the model of indirect network effects, and the influx-outflow model proposed for a competitive two-sided market, fail to adequately depict the co-dependent diffusion of innovation. Building on findings from Study 1, Study 2 (presented in Chapter 3) shows that the Bass model with churn rates could be a promising candidate for modelling the co-dependent diffusion of innovation. In the payment innovation context, the churn rate represents the user dropout as a percentage of the current user base. Results reveal that merchants exhibit a higher churn rate than consumers, and the churn rates vary by industry. Simulated churn rates show opposite impacts on the innovation effect and the imitation effect in the diffusion process, where managerial implications can be drawn on tailoring strategies to different adopting groups based on the churn rates aiming to fuel the diffusion. Study 2 also highlights the potential of using churn rates as the proxy for the feedback effects between the adopting groups.

As the interaction effect between the adopting groups is established in Study 2, Study 3 (presented in Chapter 4) applies the Vector Error Correction Model (VECM) to account for consumer and merchant usage simultaneously. In the short term, consumer usage increases as a result of the variation in merchants' usage. The positive response of consumers remains significant in the long run. On the contrary, merchants exhibit decreasing response to the variation in consumers' usage; thus, only the immediate response is strong and significant in the short run. It is worth noting that, unlike the impact of marketing mix factors on sales that will die down over time, the variation of usage in one adopting group at the early stage of the diffusion could permanently lift the usage of the other group. This provides the first robust insights into the empirical patterns of co-dependency during the diffusion of innovation in two-sided markets and demonstrates how other such markets can be studied in the future. Managers can stimulate usage on one side of the market in the early stage of the innovation growth to leverage the interaction effect between the two sides. As emerged from the current work, an early push of usage on the merchant side may drive the co-dependent diffusion of the innovation in the long run.

Acknowledgement

A good PhD is a completed Ph.D.

-- Malcolm J. Wright

When I first heard the above statement, I did not buy into it. A good PhD shall have top-tier publications, make valuable contributions to a specific area of knowledge in the studied domain, and gain significant experience in presenting ideas via attending conferences and networking with similar minds.

When I am close to the end of my PhD journey, in hindsight, I realise the wisdom of the quoted statement and my unrealistic ambitions. A good PhD needs, first and foremost, to be a completed PhD. Since then, the knowledge gained and the habit formed during the doctoral training will jointly contribute to whatever the degree holder wants to achieve in the coming years. The magic of time will catalyse changes both inside and outside.

Like almost every PhD candidate, the journey towards a doctorate is long and arduous, full of ups and downs. Like almost every PhD journey, the downs can easily outnumber the ups. When I set off in 2018, I didn't believe that it would also be my experience for the coming four years. As I look back, a bit of sarcasm mixed with a bit of relaxation, I confirm that those descriptions are not made up from thin air.

Admittedly, I underestimated the difficulty level when I embarked on the journey. To me, doing a PhD is just another four years of fun, learning whatever I want to learn and then getting a certificate for the time and effort I spared. As we are often asked, "Why PhD?", my simple, blunt, and even naïve answer was – I had a master's degree already, so I pursued a PhD as the one-step ahead. It was dangerous to step onto a brand-new track in the bush without a backpack, water supply and a very determined mind.

Luckily, I survived, submitting my work and approaching completion. I could not have reached this milestone without my supervisors' tremendous support. Thank you, my dearest supervisors: Professor Wright and Professor Wetzel.

One thing at a time.

-- Malcolm J. Wright

Malcolm, I thank you for every session you had with me, online and offline, on sunny and rainy days, and for your support and encouragement. During our first meeting, at the bench outside of the QB building, you kindly agreed to be my supervisor, guiding me through the journey that I was naïve about. In the following years, I passed the confirmation, presented at the ANZMAC at Wellington, switched to part-time in the final year, and submitted for examination. Every step, every minor achievement, you are behind me. You cleared your dairy to accommodate my needs whenever I felt behind schedule. Whenever I struggled with a paragraph or lines of code, you calmed me down by saying, "one thing at a time". It worked. It magically worked every time.

Don't sell stinky fish.

-- Hauke A. Wetzel

Hauke, I am grateful that you stayed as my co-supervisor after you moved to Sydney. On top of Malcolm's encouraging words, you added an extra layer of objectivity and strictness to everything I worked on. You pointed out the confusion part in my writing and thinking and guided me towards a better writing structure and more concise and precise wording. Due to my humble Chinese nature, I am inclined to speak low of my output, always presenting the drawbacks I found ahead of some trivial things I did well (see, here again, I downplayed the good part). But you advise me to be confident about my output as no one wants to buy stinky fish. Now I always put my best effort into everything I do to avoid selling stinky fish.

The School of Communication, Journalism and Marketing has a group of lovely people whom I will always be grateful to. Thank you, Nitha, for offering me the opportunity to be involved in the Master of Analytics program for over two years. I gained valuable insight into analytics and teaching experience both online and on campus. I met talented students, in New Zealand and virtually via our partnership program in Singapore, who showed passion for learning and shared their industrial experience. I met great colleagues, Esther and Murray, who trusted me and set up the role model for me to be a good instructor. Thank you, Jonathan, for offering to be my "backup" supervisor to make my change of supervision as smooth as possible. Thank you, Alexandra, for being a big sister and caring about the development of each PhD candidate. You are responsive whenever I have questions about my PhD journey, and you come up with various events, such as the Paper Bag Talks and workshops, to benefit

all the PhDs. I would like to thank my PhD peers, Anushka, Koursar, Mal, Andee, Alex, Phil, Simon, Chao and Martin. You are amazing souls, encouraging, and enlightening in different ways, making my PhD journey never alone.

Special thanks go to Professor van Heerde. You said, "yes, you can apply" in a 6 am morning in September, initiating my PhD journey. That day was also my birthday, when you unintentionally gave me a new start as the best birthday gift. It is a pity for me that I gave up the chance to land Sydney with you and Valentyna. However, you will always be the guiding star in my academic life and a role model whom I will always look up to.

Last but not least, I thank my families. My granny, who passed away too early to enjoy beautiful things in life and to witness my growth, sowed the seed of curiosity in me when I was little. I made my life goal to be her pride and gradually moved towards that goal as time passed. My parents, who always respect and trust me in every decision I make, are my motivation and support. They value education and encourage me to learn and develop the way I desire. My partner, who took care of all the housework while I was busy learning, teaching, writing, and working, is my emotional stabiliser and life companion. As I can be subtle and unconfident when encountering setbacks, it is my most incredible fortune to have someone willing to support me unconditionally and inject the right level of confidence into the humble me to allow me to overcome obstacles in life.

Oh! One more person to thank. I shall thank myself, who choose to finish this journey despite the turbulence at the beginning, middle, and end. I am the first one in my family to obtain a doctoral degree. I am proud of what I have achieved so far.

Learning is a lifetime journey. The completion of PhD education is never the full stop. Life continues, and so does learning.

Table of Contents

List of Figures

List of Tables

Chapter 1 Introduction

1.1 Background

1.1.1 Growth of Payment Innovation

Data from the Organization for Economic Cooperation and Development (OECD) shows that innovation investment is an increasingly growing expenditure, rising from 2.02% in 1991 to 2.68% in 2020 as a percentage of the gross domestic production (GDP) across all OECD countries (OECD, 2022). According to the OECD report, the dollar value of the investment in innovation reached 1.5 trillion US dollars in 2020 for OECD countries. Israel tops R&D spending as a percentage of GDP, with 5.44% of GDP spent on science and research, followed by Korea and Chinese Taipei. Dollar-wise, the US leads in annual R&D investment with 664 billion US dollars, and China closely follows with 553 billion US dollars per year. Given the financial resources and efforts invested in innovation, there is a parallel requirement of understanding how innovation diffuses. This knowledge requirement drives the ongoing research efforts into the diffusion of innovation over the last decades.

One key area of innovation is contactless payment methods, which have proliferated since the 2000s, disrupting consumers' default repertoire of payment methods. Payment innovation has a long history. While the invention of notes and cheques prominently improved the portability of money and made transactions easier, the introduction of magnetic-stripe card payments (i.e., payment made by debit cards, credit cards and stored value cards) initiated a giant leap in efficiency and security in the transaction process. High value transactions can now be made with a light-weight plastic card, with approval subject to the input of a PIN. People who used to pay with cash, cheques or credit/debit cards for retail purchases continue to be offered with new payment methods, including mobile payment, QR code payment and contactless card payment (i.e., Visa 'PayWave', Mastercard 'PayPass'). Meanwhile, not all payment innovation becomes automatically successful. Credit card payment was introduced to the studied country in late 1970s (Chandran et al., 2005) but still took roughly 40 years to surpass debit cards in terms of transaction value (data sourced from the statistical bureau of the studied country). Stored-value cards or prepaid cards, modelled on credit card usage, but requiring a deposit in advance, were also introduced but have not been widely distributed. Contactless payment methods therefore cannot be assumed to be automatically successful, and a further barrier complicates its diffusion, namely the requirement of joint usage from consumers and merchants. Merchants may refuse to accept a certain card type if few consumers prefer to use it and the surcharge of the card type is high. Consumers may not use a certain card type if they do not hold one (i.e., not being granted a credit card) or they think the card usage cases are limited (i.e., the single purpose stored-value cards). Nonetheless by the end of 2020, contactless payment methods had achieved 31.55% of total transactions at the checkout in the studied country.

Forecasts of the growing adoption of payment innovations have been detailed in the "Driving the Future of Payments 10 Mega Trends" issued by Accenture in 2017 (Accenture, 2017). Based on a survey with 1,000 respondents from the United States and 500 from Canada, a PwC report shows that 64% of consumers plan to use mobile wallets in 2020, up from 46% in 2017, with a 39% rise in the user base (PwC, 2021). At the end of 2020, US and Canada witnessed cashless transaction volume amounting to 180 billion in total (PwC, 2021).

Apart from the surging popularity of payment innovation in western countries, Asian countries such as China also have gained momentum in payment innovation uptake in the last decade. According to a report by Ipsos and Tencent Research Institute in 2017, the transaction volume of contactless payment (i.e., mobile payment) in China increased from 3 billion in 2013 to nearly 100 billion transactions in 2016, a 30 times increase over three years (Tencent et al., 2017). The rapid growth of contactless payment transformed China from a cash-reliant economy to a payment innovation leader fuelled by efficient and safe payment options. Based on data of the active users of WeChat Pay and Alipay, 80% Chinese people are equipped with at least one type of contactless payment device, bringing the total number of monthly active users of WeChat Pay to 1.08 billion and the annual active users of Alipay to 700 million.

The global public health crisis triggered by COVID-19 accelerated the changing landscape of the retail payment market, with a boost to contactless payment method uptake and usage due to consumers' hygiene concerns. Mobile payment options and contactless-function-enabled cards are recommended ways of paying during the pandemic as those methods help reduce physical contact at checkout. Relying on the 2020 data, PwC reports that the volume of cashless transactions is expected to double worldwide from 2020 to 2030 due to broader acceptance of card and mobile payments (PwC, 2021).

1.1.2 Studies in Payment Method Area

<u>Two-sided nature of the payment market</u>

The payment market is a typical two-sided market in which facilitators enable interactions between end-users to get the two (or multiple) sides "on board" (Rochet & Tirole, 2006). Any factor that assists usage on either side contributes to the prosperity of the whole market. Evans & Schmalensee (2005) use an excellent metaphor in their book to describe the two-sidedness of the payment market, “Just as you cannot dance the tango without a partner, a payment card needs both consumers and merchants”. This means, in the debit/credit card payment scenarios, consumers who want to pay with a debit/credit card at the checkout need the merchant to accept the debit/credit card payment to complete the transactions. In cases of mobile payment, QR code, and contactless card payment powered by the Near Field Communication (NFC) technology, if consumers choose to pay with either of those novel payment methods, merchants should have the corresponding reader to accept the payment.

In the two-sided market literature, one stream of research addresses the network externalities, also termed as the network effect (Rochet & Tirole, 2002). Defined in Katz and Shapiro (1985, 1986), network externalities specify that the utilities derived from the consumption of the goods or services increase with the number of other agents consuming the same or compatible goods or services. For stand-alone innovation, the network effects may result from direct usage and is thus called a direct network effect; for compatible innovations, the impact can arise from indirect synergetic usage and is thus called an indirect network effect. In the two-sided market context, this indirect network effect is also called cross-group network externality (Rochet & Tirole, 2006), which is believed to be key to the growth of the two-sided markets (Armstrong, 2006).

A handful of studies examine the driving forces of the cross-group network externalities in the payment market context between merchants and consumers. Lee et al. (2019) discuss the network effect of merchant acceptance and consumer adoption of mobile payment services. The study constructs an integrated model accounting for the drivers of consumer adoption and of merchant adoption. Results confirm the existence of cross-group network externalities and suggest that the payment network providers strive to maximise these externalities to enhance payment innovation adoption in the market. In a similar vein, Rysman (2007) finds that after controlling for the impact of merchant acceptance on consumer usage of a particular card payment method, characteristics of consumers such as age, income, education, and household sizes exert no impact on that card payment method usage. Ryman’s conclusion supports the argument that the payment market is two-sided with cross-group network externalities, and the magnitude of the externalities plays a significant role in determining the usage outcome.

The development of the payment market is another focus of payment market literature. High costs and not being user-friendly are critical barriers to the growth of the mobile payment market in 2006 (Ondrus & Pigneur, 2006). Through the lens of third-party payment innovation in general, Yao et al. (2018) adopt a value-added approach to evaluate the benefits of payment innovation to the economy. Their results show that payment innovation has a positive, long-term stable correlation with the value creation capability of the traditional financial industry. Martikainen et al. (2015) find that the cross-country dispersion of retail payment innovation is declining with time. The preference for payment innovation across EU countries has been shown to be similar for traditional payment methods, such as cash and credit cards. Payment method loyalty is found useful in explaining the common preference for certain payment methods (Wright, 2002). However, the common preference is yet to be proved for new payment innovations, such as e-money.

Payment Method Adoption

The theory of diffusion of innovation (DOI) proposed by Rogers (1983) is seminal in understanding how innovation is communicated through certain channels over time among members of the adopting group(s). Rogers's theory offers five innovation characteristics as critical determinants of the rate of adoption of innovation, including 1) relative advantage, 2) compatibility, 3) complexity, 4) trialability, and 5) observability. Empirical studies on payment method adoption draw from DOI and customise to fit the specific context. Mallat (2007) is among the early papers that built on DOI to investigate the determinants of mobile payment adoption and finds the relative advantage of mobile payment as a strong predictor of consumers' intention to adopt. Johnson et al. (2018) corroborate the effect of relative advantage on the intention to use mobile payment with 270 valid responses from an online survey.

The Technology Acceptance Model (TAM) proposed in Davis (1989) is one of the most widely used models in payment adoption studies (e.g., Leong et al., 2013; Liébana-Cabanillas et al., 2014; Plouffe et al., 2001). The model proposes a parsimonious modelling form with two predictors of the intention to adopt: perceived ease of use and perceived usefulness. These two factors have been extensively examined and confirmed as critical factors in the payment innovation adoption (De Luna et al., 2018; Kalinic et al., 2019; C. Kim et al., 2010; Leong et al., 2013). Perceived ease of use tends to impact perceived usefulness and attitudes towards usage. In contrast, perceived usefulness affects attitudes, which further influences the intention to adopt based on the Theory of Planned Behaviour (TPB) (Ajzen, 1991).

Massive research builds on the framework of TAM with additional factors. On top of the determinants constructed within TAM, security and social environmental impacts are also found influential. Factors that are security-related include perceived security, perceived risk, and trust. The level of trust and the trust-building process determine online credit card usage and mobile payment adoption (Kim et al., 2010; Shao et al., 2019; Shu & Cheng, 2012). Singh & Sinha (2020) find small but significant effect of perceived trust on the merchants' acceptance of mobile wallets. In addition, social image and subjective norms affect the intention to adopt, citing the social environment as the source of influence (Leong et al. 2013; Liébana-Cabanillas et al. 2014). As paying at the checkout of a retail store or a café place is visible to both adopters and non-adopters nearby, people may reflect on whether to adopt or disadopt upon witnessing others' decisions.

Another extensively used model is the Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003). This model builds on eight prominent theories and models in the technology adoption literature by combining and refining key factors from prior knowledge. The model specifies four core determinants, including performance expectancy, effort expectancy, social influence and facilitating conditions, and four demographic factors serving as the moderators of intention to adopt. The UTAUT has received popularity in recent payment adoption research, mainly due to the improved explanatory power associated with the increased number of predictors (e.g., Khalilzadeh et al., 2017; Slade et al., 2015). Another benefit of UTAUT lies in the linkage between the pre-adoption expectation to the post-adoption evaluation through the expectancy of performance and effort. An extension of UTAUT, namely UTAUT2, is proposed in Venkatesh, Thong, and Xu (2012), which further incorporates price value, hedonic motivation and habit into the model. This framework serves as the basis for a selection of work in the payment area, including Oliveira et al. (2016), Koenig-Lewis et al. (2015) and Hussain et al. (2019). Although the UTAUT and UTAUT2 frameworks incorporate more factors to explain adoption, the key influential factors, i.e., the security-related factors and social-related factors, under these two do not differ much from the studies based on TAM (Khalilzadeh et al., 2017; Oliveira et al., 2016; Shin, 2009). Therefore, the accumulative adoption work is collectively criticised for lack of theoretical advancement (Dahlberg et al., 2015).

Apart from adoption driven by free-will, forced adoption, frequently found in the organizational adoption context has been studied by Ram & Jung (1991). A typical example of force adoption can be found in the organizational adoption of technology system, where individuals are required to adopt the system, usually within a short period of notification, to comply with organizational requirement of compatibility. Ram & Jung (1991) find that individuals tend to resist the innovation if forced to adopt, while the resistance can be attenuated if organizations offer a trial of the innovation and the if communication mechanisms are in place for individual feedback. In the context of payment innovation, we deem that as consumers and merchants in general circumstances are free to choose their payment method, and normally there is more than one way of paying to choose from, force adoption is rare. Merchants who want to realise sales at the checkout usually offer multiple acceptable payment methods to enhance payment compatibility.

In the domain of service innovation, postadoption usage and disadoption is critical in determining the profitability and popularity of the services in the long run, especially for those services charged on the continuance usage basis (Libai et al., 2009; Kumar & Reinartz 2018) . A handful of research examines determinants of services disadoption, finding ease of use and experience as prominent drivers (Prins et al. 2009; Shih & Venkatesh 2004).

On top of the massive efforts paid to understanding the drivers of payment innovation adoption, studies also investigate why the usage of certain novel payment methods fails to meet expectations. The main inhibitors identified include lack of trust, high perceived risk, surging costs, and lack of compatibility market-wide (Humbani & Wiese, 2019; Johnson et al., 2018; Sharma et al., 2018). For new technologies, such as cryptocurrency payment, the lack of consumer demand tends to be the main barrier (Jonker, 2019).

Payment Methods and Consumer Spending

Payment methods are found to be associated with consumer spending. Studies report a relationship between spending escalation and the chosen payment method for the purchase (i.e., Feinberg, 1986; Hirschman, 1979; Raghubir & Srivastava, 2008). Hirschman (1979) is a pioneering piece that examines the relationship between consumer spending and the payment methods consumers utilise. The author identifies an association between the payment method of choice and the spending amount as well as frequency. People paying with a card tend to spend more and spend more frequently than people with cash, and people with multiple cards tend to spend more than those with one card. Feinberg (1986) conditions the experiment participants with the image of a credit card and shows that merely thinking that the purchase can be paid with credit cards will entice people to spend more. Although this finding is challenged in studies such as Shimp & Moody (2000) and Liu & Dewitte (2021), where the attempts to replicate the findings all failed, the idea of associating credit card payment with increased spending is still widely acknowledged. Soman & Cheema (2002) show that increasing the credit limit, a unique feature associated with credit payment, increases spending, as the credit limit offers an additional source of funds to spend. Thomas et al. (2011) conclude that credit cards, compared with cash, curb fewer impulsive purchases, and thus lead to higher basket values.

As payment formats evolve from traditional paper-based to card-based and then mobile-based, studies attempt to draw a connection between different payment formats and consumers' spending outcomes. Extending the knowledge of card payment on spending escalation, researchers study the mobile payment and mobile wallets in a similar way as they did with cards and cash, and conclude that mobile payment methods contribute to greater willingness to pay and larger size of basket values (Falk et al., 2016; Liu & Dewitte, 2021). Results attribute the increased willingness to pay to both the payment formats and the decoupling of paying from the purchasing process.

A stream of research relies on the notion of pain of paying to explain the relationship between the payment methods in use and consumer spending. Pain of paying, proposed in Zellermayer (1997), describes the displeasure experienced by consumers when they make the payment for their purchases. A lower level of pain of paying tends to result in greater consumer spending (Prelec & Loewenstein, 1998). Different payment methods are compared based on the transparency of wealth depletion and memory cues on spending to determine the corresponding levels of pain associated with paying (Soman, 2001). Cash payment transparently shows the depletion of wealth, making people clearly aware of the money being spent and thus incurring strong pain of paying. Card payment, in contrast, deducts money from the account balance, making the wealth depletion less noticeable and thus less transparent, less pain of paying. In addition, researchers find that when people pay with cards, they are less likely to recall the exact amount of their spending as the memorial cues are weaker than with cash (Raghubir & Srivastava, 2008, 2009; Soman, 2003; Soman & Cheema, 2002). Therefore, a transparent payment method with a memorial cue incurs strong pain of paying, and consequently curbs the willingness to spend. Results show cash to be the most transparent payment instrument, followed by cheques and various card payments, and mobile payment comes last (Falk et al., 2016; Soman, 2003). By controlling cash-on-hand, Runnemark et al. (2015) compare the willingness to purchase identical products among people who pay with debit cards and cash. Debit card payment is found associated with higher willingness to purchase than cash due to the lower level of transparency, given similarity between the two methods in terms of immediate depletion of wealth.

When examining the effect of payment method choices on consumer spending behaviour, studies tend to assume that the payment method of interest, such as the mobile wallet, has been widely adopted (Kumar et al., 2019). However, this assumption needs to be evaluated before being taken for granted. Research about the impact of payment methods on spending behaviours fails to have a solid root before the diffusion is well understood, lest the growth of adoption confounding the measurement of consumer spending for that payment method. For new payment methods, whether the market will widely adopt the specific way of paying ought to be modelled and forecasted first. Then comes the evaluation of the impact of the adoption and usage on consumer behaviour.

In sum, prior knowledge of payment method innovation focuses on three main areas: the two-sidedness of payment market, the various drivers of payment innovation adoption and the effect of payment method choice on consumer spending behaviour. It remains unknown how the payment method innovation diffuses in the retailing context and what is the effective modelling approach to describe the diffusion of innovation of this type. One close attempt is Antonides, Bas Amesz, and Hulscher (1999), which utilises transaction data of ATMs and banker's cards across ten countries between 1978 to 1996 to describe the diffusion of ATM and banker’s cards. However, no effort was made to depict how different adopting groups of payment innovation interact with each other along the innovation diffusion process. The current thesis aims to fill this gap.

1.2 Thesis Key Concepts and Definitions

Payment innovation involves a two-sided market where the successful adoption and use of the innovation requires joint efforts from both the consumer and merchant sides. Whenever consumers want to utilise the innovation to pay, merchants need to accept the chosen method to enable the transaction. Unlike most diffusion research focusing on the consumer market, the diffusion of payment innovation demands to focus on two adopting groups in a two-sided market. Based on the literature survey, knowledge regarding how innovation diffuses in a two-sided market is scant. Therefore, in the following section, we first present the introduction of contactless payment coming after the emergence of debit and credit cards. Then we present the definition of a new type of innovation – co-dependent innovation – that describes the contactless payment method innovation.

1.2.1 Contactless Payment Methods

Smart Card Alliance (2003) defines contactless payment as the ability to perform a non-cash payment transaction without a physical connection between the consumer payment device and the physical point of sale (POS) terminal. This definition identifies two critical parts that jointly enable the contactless payment innovation: the consumer payment device and the merchant POS terminal. The current study includes contactless-enabled cards and mobile devices with Near Field Communication (NFC) function as the consumer payment devices, and contactless-enabled POS terminals as the terminal of interest. A contactless payment transaction is completed when the consumer and merchant who each possesses the contactless version of the device and decides to use it at the checkout. A card payer will not automatically become a contactless payer unless s/he knowingly chooses to use this feature with the enabled card. The same applies to a merchant who runs one or more POS terminals and chooses to accept payment by contactless cards. Therefore, usage decision needs to come from both enabling parties and the decision of consumers to use appears to be conditioned on merchants' decision to use, and vice versa.

1.2.2 Co-dependent diffusion of Innovation

Drawn from Rogers's idea of technology cluster, we define co-dependent innovation as two or more innovations (components) with each requiring the presence of the other to enable the innovation to function. Payment method innovations such as contactless payment methods fall into this category, as their functioning requires joint uptake of contactless payment devices by consumers and contactless-enabled terminals by merchants. Other pairs of innovations, such as electronic vehicles and charging stations, whose functionality requires uptake from different adopting groups, can also be considered as co-dependent innovations. In the seminal work of Rogers (2003), the author proposed the idea of technology clusters to depict one or more distinguishable but closely interrelated elements of technology as one cluster. Technology clusters will enhance the rate of adoption of innovations that form parts of the cluster (Shih & Venkatesh, 2004). To be specific, Peterson & Mahajan (1978) classify four types of innovation in this context: 1) independent innovation, 2) contingent innovation, 3) complementary innovation, and 4) substitute innovation, based on the relationship between two innovations. The idea of co-dependency may sound similar to the idea of complementary, as complementarity depicts two innovations that are compatible and can be used together, such as the computer and internet, the microwave oven and microwave meals. However, the co-dependency we introduce here features the paired innovations with the necessity to be used in combination to gain utility. This co-dependency goes beyond simple compatibility and shall be studied separately.

We also define co-dependent adopting groups as two or more groups that each requires the adoption by the other to enable innovation usage. The definition does not necessarily indicate that the adopters have fixed roles during the diffusion of co-dependent innovation but suggest that to enable the functioning of the innovation, adopters shall be classified explicitly into two or more groups.

Building on those two definitions, the idea of co-dependent diffusion flows out naturally. The co-dependent diffusion of innovation describes the growth of co-dependent innovation as the result of the joint uptake by the co-dependent adopting groups. The paired innovations adopted solely by consumers, such as game consoles and game titles, CDs and CD players, are thus not fit for the co-dependent definition.

1.3 Problem Statement and Contribution

1.3.1 Problem Statement

The current thesis aims to understand how co-dependent innovation diffuses in a two-sided market. Empirically, the work examines the diffusion of contactless payment innovation in the retailing context. Novel payment methods fit the definition of co-dependent innovation, and the payment market is a typical two-sided market that accommodates two adopting groups (Rysman, 2007). Therefore, a study of the diffusion of the contactless payment innovation could bridge the gap between prior knowledge of drivers of payment innovation adoption and the aggregate pattern of payment method diffusion. The study also provides a steppingstone for future studies in the area of co-dependent innovation diffusion in other non-payment contexts. Given the disruptive nature of new co-dependent technologies, a better understanding of the diffusion of co-dependent innovations is urgently needed.

We state the overarching question of the thesis as being to examine:

- How does co-dependent innovation diffuse in a two-sided market, and what modelling approach can be used to explain the co-dependent diffusion pattern?

To answer this question, we first introduce the idea of co-dependent innovation and the co-dependent diffusion of innovation. The terminology has been briefly included in the 1.2 Thesis Key Concepts and Definition section and will be covered in depth in the following chapters.

Specific research questions in the thesis are listed as follows, all of which will be addressed in the three studies presented in the subsequent chapters.

RQ1: What mechanism(s) underlying the interrelated or platform-based innovations can be used to explain the co-dependent diffusion of payment method innovation? Do existing models perform adequately in the context of co-dependent diffusion?

RQ2: Can the Bass model proposed for service innovation be used to depict the co-dependent service innovation? If yes, what can be used to explain the interaction between adopting groups?

RQ3: How does the co-dependency between the adopting groups impact the co-dependent diffusion over time?

1.3.2 Contributions

This thesis makes theoretical and managerial contributions to the marketing literature with a focus on the diffusion of innovation. First, the thesis contributes to payment literature by modelling the diffusion of payment innovation with quantitative time series purchase data. As most of the extant payment literature focuses on testing the drivers of the willingness to adopt (i.e., De Kerviler, Demoulin, and Zidda 2016; Kim, Mirusmonov, and Lee 2010; Oliveira et al. 2016), the current work pioneers in applying econometric modelling with transaction data to understand the diffusion of payment method innovation. The modelling framework attempts to account for the co-dependency between the distinct adopting groups along the diffusion paths. The output depicts the co-dependent diffusion at market level over time instead of merely suggesting the intention to adopt from both sides.

Second, the thesis contributes to the service literature by testing the effect of churn in the context of co-dependent service diffusion. Apart from Libai, Muller, and Peres (2009), the diffusion literature rarely taps into the service industry and thus falls short in advancing the knowledge for new business modes such as sharing economy and emerging innovation types such as co-dependent innovation (Peres et al., 2010). The increased availability of service data facilitates more research efforts in this area. Utilising the payment data that accounts for consumer and merchant usage separately, the current work proposes the churn rates as the proxy for the co-dependency between adopting groups and shows how churn rates differ by industries for merchants.

The third contribution lies in the conceptual and methodological development of studying co-dependent diffusion of innovation. The current research is dedicated to the co-dependent type of innovation, a promising category expecting to proliferate in the digitalised economy. With the mounting number of innovations that require joint efforts from more than one adopting group for the innovation to thrive, it is critical for researchers to clearly define the innovation type and study the diffusion pattern with a dedicated modelling approach. For instance, by identifying two adopting groups, research on co-dependent innovation shall exclude the cases of video game consoles and game titles, as the ultimate adopters of the complementary consoles and games are down to consumers only. Future studies on electronic vehicles and digital currencies can draw from the knowledge developed in the co-dependent innovation domain, given the shared characteristics and facilitating requirements of those innovations.

In addition to the theoretical advancement, the empirical results presented in the work add substantive evidence to the area of co-dependent diffusion. Results demonstrate the importance of accounting for the churn rates in the co-dependent service innovation diffusion and show divergent churn rates for each adopting group in the diffusion process. Neglecting the churn rates can lead to underestimated growth potential for the innovation for each group. Furthermore, results based on the co-dependent time series modelling provide guidance to service operators regarding whom to target first at different stages of diffusion. Prior research mainly considers only one side of the market and thus fails to describe the complete picture of diffusion and accounts for the interaction between the adopting groups. By examining both sides of the market in a co-dependent innovation scenario, our findings cover the interaction between the adopting groups and depict the temporal lead-and-lag effect regarding the diffusion outcome, filling the missing piece of the puzzle that is previously understudied.

1.4 Structure of the Thesis

This thesis strives to answer the proposed research questions with three independent studies in the following chapters. We leverage a rich transaction data set that contains 70% of the point-of-sale transactions for all digitalised payment methods in a retailing context in a developed western economy. The data will be applied to all three studies with tailored manipulation. Chapter 2 (i.e., study 1) is a replication study that aims to test whether extant models and mechanisms can be used to explain the co-dependent diffusion of innovation. Specifically, in this chapter, we review the relevant research streams in the literature and select three typical pieces of modelling work that can be good candidates for depicting the diffusion of payment innovation. We adopt the differentiated replication approach to reproduce the results of established models with our payment transaction data. Chapter 3 (i.e., study 2) builds on the replication output and further explores how payment diffusion can be modelled from both the consumer and the merchant sides under the diffusion of service innovation framework. Literature shows that the diffusion of innovation among the merchant group has been largely understudied. Therefore, our second study emphasises the merchant side diffusion and compares merchant diffusion patterns across multiple industries to fill the knowledge. The third study is presented in Chapter 4. Building on the limitations identified from replication studies and the Bass modelling approach, we pursue a time-series modelling approach – Vector

Error Correction Model (VECM) – to account for the interaction between the adopting groups and to depict the lead-and-lag effect between the two groups in the co-dependent diffusion.

We present the conclusion in Chapter 5, with theoretical and managerial implications derived from the three studies. We then discuss potential limitations of the research, which echo the potential venues for future study in diffusion of co-dependent innovation. The current thesis also demonstrates the research process from the known to the unknown, from the established models and methodologies to the newly built modelling framework in the promising area of study.

Chapter 2: Modelling the Uptake of New Payment Methods

Abstract

Choosing a way to pay is integral to consumers' shopping experience. Studies have examined how consumer characteristics affect this choice and how different payment methods shape consumer behaviours, e.g., credit cards offering credit that stimulates consumer spending. However, the proliferation of new online and contactless payment methods presents new challenges to understanding payment choices. One challenge lies in the diffusion of such payment methods, as they require the joint uptake of different components of the system by consumers and merchants, respectively. Those components are complementary and co-dependent. Little work has been done in this area. However, there are relevant studies in other industries, such as Bucklin and Sengupta's (1993b) analysis of co-diffusion effects for retail scanners and Universal Packaging Code (UPC), Stremersch et al.'s (2007) analysis of indirect network effects for consumer electronics and associated titles or programs, and Hinz et al.'s (2020) analysis of network effects for online platforms accounting for customer acquisition and dropout. As the generalizability of these prior studies to the context of payment methods is unknown, we conduct a differentiated replication using eight years of transaction data from a developed western economy. Results show that 1) Bucklin and Sengupta (1993b)'s Bass model approach explains payment method diffusion within each adopting group but fails to explain the interaction between the adopting groups, 2) the asymmetric indirect network effects proposed in Stremersch et al. (2007) present symmetrically in the payment context, and 3) Hinz et al.'s (2020) accounting for customer acquisition and dropout continues to be relevant, but their single lag model structure fails to account for the dynamics presented in payment innovation diffusion. While these findings demonstrate limited generalizability of past work on modelling payment method diffusion, they do point to fruitful directions for future research in this area; for example, to investigate the effect of generalizing the Bass model approach to include customer dropout, and to expand the analysis of co-dependency to include multiple periods of asymmetric lags.

Keywords:

Payment innovation, diffusion of innovation, co-dependent diffusion of innovation, two-sided market, replication study

2.1 Introduction

Shopping trips are usually concluded with transactions enabled by a particular payment method, making the chosen way of paying an integral part of the retail experience (Bell & Lattin, 1998). Although consumers may not be aware of the critical role of payment methods in nudging their purchasing behaviour, researchers in the payment area have spent considerable effort in examining how consumer purchases are impacted by the choice of payment methods (i.e., Feinberg, 1986; Greenacre & Akbar, 2019; Hafalir & Loewenstein, 2011; Prelec & Simester, 2001; Shah et al., 2016; Siemens, 2007; Thomas et al., 2011). For instance, Kumar et al. (2019) explore the impact of add-on features of mobile wallets on retail customer engagement, assuming mobile wallets are widely adopted by consumers. This assumption of sufficient diffusion of a certain payment innovation is shared among the payment studies, where the successful diffusion is typically assumed rather than modelled. The question of how payment innovation diffuses over time as the result of the changing behaviours of the adopting groups has not been explicitly answered.

Diffusion of payment innovation relies on two adopting groups (consumers and merchants), each adopting a separate component to jointly enable the usage of the innovation. We term this type of innovation as co-dependent innovation, with two or more innovations (components) requiring the presence of the other to function. Diffusion is then the result of the joint uptake of the innovations or components of the system by two or more co-dependent adopting groups. For example, a payment method innovation in the retailing context usually constitutes a payment device adopted by consumers and a payment receiver adopted by merchants. Therefore, payment method innovation fits the concept of co-dependent innovation, and so do other emerging innovations, such as electronic vehicles and charging stations. A key aspect of co-dependency is that utilities obtained by one adopting group will depend on the depth of diffusion among the other adopting group. This creates key uncertainties – which group acts first, and how does uptake rachet up between the co-dependent groups?

Peterson and Mahajan (1978) categorise two or more products based on the relationship between them into independent, contingent, complementary and substitute products. Co-dependency is clearly not consistent with independent or substitute products. Being contingent implies the adoption of one product precedes that of the other, which is not the case with payment methods, as there is no specification of cards being adopted earlier than terminals or the other way around. Co-dependency may resemble complementarity, in which two innovations are compatible and can be used together, such as the computer and internet, wireless voice and data device (Dewan et al., 2010; Niculescu & Whang, 2012). However, unlike complementarity, co-dependency features innovations that need to be used in combination by two adopting groups simultaneously to gain any utility. This goes beyond simple compatibility and thus calls for additional research, as none of the prior classifications incorporates the necessity of being both complementary, i.e., can be used together, and symmetrically contingent, i.e., must be used at the same time.

Despite the importance of understanding payment innovation diffusion as an example of co-dependent innovation, knowledge in the area is scarce. Few studies model how payment innovation diffuses among adopting groups, with the exception of Antonides, Bas Amesz, and Hulscher (1999), who model the diffusion of ATM usage and banker's cards in European countries. Building on the linearised Bass model (Bass, 1969), the authors conclude that the diffusion of the four payment systems under study is mainly driven by the internal influence, such as social learning. The work models the general adoption outcome, without differentiating consumers' adoption from merchants' adoption. To our best knowledge, no prior work models payment innovation diffusion accounting for co-dependency – that is with explicit consideration of the distinct adopting groups and the interaction between them. As an initial approach to this problem, we identify mechanisms from other contexts with potential to describe co-dependent diffusion and undertake a differentiated replication to assess the generalisability of these mechanisms to the context of payment data. The objective is to determine whether the mechanisms proposed in prior work can adequately describe how payment innovation diffuses as the result of the interaction between the adopting groups. Key questions are:

- What mechanism(s) underlying the interrelated or platform-based innovations can be used to explain the co-dependent diffusion of payment method innovation?
- Do existing models perform adequately in the context of co-dependent diffusion?

Given the limited discussion of diffusion of payment method innovation in the payment literature, we resort to literature of complementary innovation, new product growth in the hardware-software paradigm as well as the growth of two-sided markets for relevant examples that can shed light on the modelling of payment method diffusion. Specifically, diffusion of complementary innovation is relevant due to the obvious overlap of complementary and co-dependent innovation. We draw on the network effects identified in the hardware-software dyads as well as the platform-based markets, given that the diffusion involves more than one party. Based on the literature and its connection to our research questions, we select three replication targets – Bucklin & Sengupta (1993b) who studied the diffusion of complementary innovation, Stremersch et al. (2007) who examine the hardware-software paradigm, and Hinz et al. (2020) who examined a two-sided market.

Results show that our differentiated replication efforts fail to fully replicate the findings of all three studies. The Bass model approach adopted in Bucklin and Sengupta (1993b) succeeds in explaining the diffusion of single innovation within one adopting group. Still, it fails to explain the interaction between adopting groups when co-dependent innovation is involved. Stremersch and his colleagues conclude that the two-way indirect network effects are rare in the consumer market, while we confirm the symmetric two-way network effects in the co-dependent innovation diffusion. Although accounting for influx and outflow for service innovation is theoretically sound, our replication fails to corroborate the generalizability of the influx-outflow model proposed in Hinz et al. (2020) with payment data, as our results only echo two out of the eight proposed relationships. A summary of the replication results is presented as follows.

Replication of	Replication Conclusion	Modelling Framework	Tested Relationship/Mechanisms in Original Studies	Original Studies	Replication
Bucklin and Sengupta (1993b)	Partially replicated	Multi-product Bass model	Bass model for independent diffusion	√	√
			One-way co-diffusion effects	√	**X**
			Two-way co-diffusion effects	√	**X**
Stremersch et al. (2007)	Partially replicated	Time-series based system of equations	Hardware installed base stimulates software availability	√	√
			Software availability stimulates hardware sales	**X**	√
Hinz et al. (2020)	Partially replicated	Symmetric single lag structure of system of equations	Same-side network effects on influx	√	**X**
			Same-side network effects on outflow	√	√
			Cross-side network effects on influx	√	√
			Cross-side network effects on outflow	√	**X**

Table 1 Summary of Replication Results

In the following sections, we review the literature on payment methods and unveil the gap in the knowledge that we aim to fill via the replication attempts. Then we describe the study framework and introduce the data set employed, followed by details of each of the three differentiated replication studies. We conclude each replication with a short discussion on the key findings, emphasizing what is adaptable and what needs improvement. Theoretical and empirical implications, limitations and future research directions are provided at the end.

2.2 Literature Review

2.2.1 Payment Market

The payment market is a typical two-sided market, defined as a market in which one or several platforms enables interactions between end-users and tries to get the two (or multiple) sides “on-board” with dedicated activities on each side (Rochet & Tirole, 2006). As a result, any factor that can assist either side with usage could contribute to the prosperity of the whole market. Evans & Schmalensee (2005) use an excellent metaphor in their book to describe the two-sidedness of the payment market, “Just as you cannot dance the tango without a partner, a payment card needs both consumers and merchants”. Hence, in a two-sided payment market, merchants’ acceptance of a particular payment method encourages consumers’ usage of this method and vice versa. This interactive relationship between merchants and consumers, later being expanded into a multi-sided payment ecosystem, attracts considerable research attention.

One prominent stream of research in the payment market literature addresses the network externalities, also called the network effect (Rochet & Tirole, 2002). The notion of network externalities, proposed by Katz & Shapiro (1985;1986), describes the utilities derived by one group of users from consuming a network-based product or service being dependent on the number of other users in the same network or cluster. Therefore, in the context of a payment market, the utilities derived from utilising a novel payment method depend on both the number of consumers who are willing to pay with the method and the number of merchants who are willing to accept the same method.

Rochet and Tirole (2006) expand the idea of network externalities into cross-group network externality, usage externality and membership externality and discuss each type in details. A cross-group network externality indicates that the number of users on one side positively affecting the number of users on the other side (Rochet and Tirole 2006). In the realm of payment methods, several studies examine the driving forces of the cross-group network externalities between merchants and consumers. Lee, Ryu and Lee (2019) examine the network effect of merchants’ and consumers’ intention to use mobile payment services with survey data. Their results confirm the interactive effect between the two sides and imply that network providers should notice and strive to maximise the network effect to enhance emerging payment adoption in the market. On the consumer side, results show that merchant acceptance directly impacts consumers’ attitude towards mobile payment service and further impacts consumers’ intention to use mobile payment. An indirect network effect, defined as the synergetic effect derived beyond the usage of the service under study to include additional complimentary services as well, is confirmed to have a positive impact on consumers' perceived usefulness of mobile payment services. On the merchant side, the direct effect of consumer adoption, together with other factors such as brand value and perceived ease of use contributes to the merchants' intention to accept the payment innovation. In summary, a two-way influence has been established in the study, confirming the existence of cross-group network externalities. Rysman (2007) identifies a positive feedback loop between consumer usage and merchant acceptance of a particular card payment method, supporting the argument that the payment market is two-sided with the presence of cross-group network externalities. The author finds that consumers concentrate on their chosen payment method and prefer to have a repertoire of payment alternatives merely as backups. Results also show that after controlling the effect of merchant acceptance on consumer usage of the card payment, characteristics of consumers such as age, income, education and household size exert no impact on the payment method usage.

2.2.2 Payment Adoption

Payment method literature shows considerable research efforts in understanding factors that drive payment innovation adoption, covering card payment adoption since 1990s and mobile payment as well as Near Field Communication (NFC) payment since 2010s (Antonides et al., 1999; Arango et al., 2015; Ching & Hayashi, 2010; Kim et al., 2010; Oliveira et al., 2016; Qi & Yang, 2003; Stavins, 2018). This stream of payment adoption builds extensively on theoretical frameworks such as Diffusion of Innovation (Rogers, 2003), the Technology Acceptance Model (Davis, 1989) and its extension (Venkatesh & Davis, 2000), and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) and its extensions (Venkatesh et al., 2012). Common drivers for adoption of payment innovation, including contactless-enabled card payment and mobile wallets, include perceived ease of use, trust, security, and social influence (e.g., De Kerviler et al., 2016; Leong et al., 2013; Oliveira et al., 2016; Plouffe et al., 2001; Shin, 2009).

Perceived ease of use refers to the degree to which the prospective users expect the technology to be free of effort (Davis et al., 1989) and is further argued to be the precedence of the perceived usefulness (Davis, 1989). Given the casual influence of perceived ease of use on perceived usefulness, this factor is seen as fundamental in technology adoption. Moreover, studies find trust to be a key driver of potential adoption, given that trust helps the adopting individuals overcome or at least attenuate uncertainties of the innovation (Corritore et al., 2003). Another factor that is closely related to trust is security. Consumers' security concerns in payment innovation are mainly directed towards the personal information stored within the payment instrument, which could enable money transfer without payer's verification (Sharma et al., 2018). Social influence reflects adopters' impact on non-adopters' uptake of the innovation, and this influence can occur either through word-of-mouth recommendation or through visibility, as it is visible to people around the payer when a certain payment method is used at the checkout.

Although considerable in volume, existing payment adoption literature concentrates on the determinants testing for the likelihood to adopt based on the framework of established theories mentioned above. Context-specific factors are examined for their impacts on adoption, and those factors come from either the features of the innovation or the characteristics of the adopting groups (Kim et al., 2010; Liébana-Cabanillas et al., 2014). The timing of adoption and the aggregate level of adoption over time, namely the diffusion of the innovation, have not been systematically studied. Moreover, most adopting studies focus solely on one adopting group, even though multiple social systems are involved in the diffusion process. In the payment innovation context, although diffusion requires the joint adoption effort of both consumers and merchants, researchers appear to pay overwhelming attention to the consumer side only. Exceptions include Au & Kauffman (2008) and Plouffe et al. (2001), as the former propose a holistic framework to examine the economic gains and losses for consumers and merchants along the diffusion of mobile payment in the market, and the latter conclude that the bottom line is critical for merchants when considering payment innovation uptake.

In sum, prior research on payment methods principally examined context-specific factors on consumers' likelihood of adoption for payment methods and used the payment market as an application of two-sided market. To our best knowledge, there is little research examining the diffusion of payment innovation in a retailing context that considers the uptake by both merchants and consumers, the interplay between the two groups, and the diffusion path of the innovation over time. This study aims to fill this gap.

2.3 Overview of Study Framework

2.3.1 Brief on Differentiated Replication

As limited diffusion modelling work is found in the payment method literature, we expand the search for modelling candidates to related areas with product/services similar to co-dependent innovation or the context of two-sided markets. Tying back to the current study, the focus is laid on whether the models used in the prior relevant work will also show generalizability for accommodating secondary data from the payment industry, determined through attempts to replicate the mechanisms.

Uncles & Kwok (2013) summarise three forms of replication, including exact replication attempts to repeat the study with the same data and close replication to allow slight deviation. Those two forms can be considered strict tests of the power of the original work. Uncles & Kwok (2013) highlight a third form of replication – differentiated replication – which tests the existing knowledge in new conditions. As science is about demonstrating empirical generalizability, differentiated replication serves this purpose well by testing the boundary of existing knowledge with new data and scenarios (Hubbard et al., 1998). Given the scarce knowledge about modelling the diffusion of co-dependent innovations such as payment methods, the current study adopts differentiated replication to test the generalizability of mechanisms used in other contexts to payment innovation diffusion.

Three pieces of modelling work emerge as the best candidates for differentiation replication. Bucklin and Sengupta (1993b) examine the diffusion of complementary innovation within two adopting groups. The authors term the interaction between the demand of the innovation as the co-diffusion effect and model this effect under the framework of the Bass model with a focus on the multiple-product growth mechanism (Peterson and Mahajan 1978). As the payment innovation shares the commonality of complementary innovation adopted by two distinct groups, we include the mechanism (i.e., co-diffusion effect) proposed in Bucklin and Sengupta (1993b) work as one of the candidates for explaining the co-dependent diffusion.

The second candidate is the time-series model built for indirect network effects in Stremersch et al. (2007). The original definition of network externalities, interchangeably called network effects, describes the increased utilities derived by users upon the increased number of other users in the same network (Katz & Shapiro, 1985). In empirical studies, however, sales, shipments, or the number of subscriptions can be used as the proxy for the outcome of network externalities, as consumer utilities or benefits can be too subjective to quantify. In a similar vein, Stremersch et al. (2007) assume that the software availability and hardware sales could represent consumers' utility gain from the adoption and are comfortable that both measurements incur no subjective judgment. The authors utilise a system of equations to answer whether there are feedback effects between the hardware demand and the software supply, which innovation kicks off the growth first, and whether the other follows. In the payment context, if the model works as expected, it will provide valuable knowledge about the temporal pattern of the co-dependent innovation growth, and thus inform payment network providers about whom to target first to stimulate diffusion. Although ample studies have been theorizing the network effects, either direct or indirect (Katz & Shapiro, 1986, 1994), Stremersch et al. (2007) pioneer in testing the existence of indirect network effects with data from nine industries from the innovation introduction stage. Therefore, fitting the payment data into the proposed time-series model will help our understanding of whether the model can be used to describe the diffusion of payment innovation and shed light on the role of network effects in the co-dependent diffusion of innovation.

The third modelling candidate is Hinz et al. (2020) drawn from the literature regarding two-sided markets. The mechanism proposed in Hinz et al. (2020) focuses on the same-side and the cross-side network effects and tries to disentangle the impact of influx and outflow users on the user-base growth on both sides of the market. The authors assume that only existing users of the platform-based market can spread the word-of-mouth about the market. By distinguishing the influx and outflow of users, rather than measuring the net users increase, the model proves to have better explanatory power than models that do not distinguish new adopters and dropouts. As the payment market is a typically two-sided market catering to both merchant users and consumer users, we deem the mechanism proposed for understanding a two-sided market could be applicable in our scenario. As with studies on network effects, the amount of theoretical work on two-sided markets exceeds the number of empirical studies, making the present study a valuable contribution of substantive evidence in the field. The following table summarises the key features of the replicated studies.

Study	Study Context	Type of underlying mechanism	Key Decision Maker	Direction of Effect	Modelling outcome
Bucklin and Sengupta (1993b)	Business to business context	Co-diffusion effect	Retailers and manufacturers	Positive	Manufacturer and retailer demand
Stremersch et al. (2007)	Consumer electronics categories	Indirect network effect	Consumers	Positive but small in magnitude	Hardware demand, and software availability
Hinz et al. (2020)	Online auction platform	Direct and indirect network effects	Buyers and sellers	Positive and negative	Buyer and seller demand
Current study	Payment acceptance and usage	Direct and indirect network effects	Consumers and merchants	Positive and negative	Merchant and consumer demand

Table 2 Summary of Replicated Studies

2.3.2 General Data Description

Our data provider, who wishes to stay anonymous, operates the payment network that handles around 70% of electronic transactions in a developed western country. Payments made at the in-store point of sale (POS) terminals and through the internet (i.e., online payment) are recorded by the provider's system. In the current study, we examine the contactless payment innovation, which is limited to the chip cards that utilise Near Field Communication (NFC) technology to pay at the in-store POS. Contactless payment methods enable payers to pay for purchases under a certain spending limit with merely a tap between the cards and the POS terminals. This novel way of paying was first introduced to the studied country in late 2011 and reached the one-million transaction milestone at the end of 2013. Therefore, to study the diffusion of contactless payment innovation, we extract the transaction data with information on individual card IDs and merchant terminal IDs between years 2012-2020, covering the introduction and take-off periods of the innovation. Data prior to 2012 is excluded due to the change of configuration in the provider's system. To avoid the compounding impact of COVID-19 starting in the second quarter of 2020, we discard all data after March 2020.
The data is obtained at the monthly level for the replication of Hinz et al. (2020). The diffusion of cards is determined by the count of distinct card IDs in contactless transactions each month, and the diffusion of terminals by the distinct terminal IDs. Card IDs used in the current month that were not used in the past three months are considered as card influx and a similar approach for the terminal influx. Note that the original work by Hinz et al. (2020) uses weekly data for four years (i.e., data points = 209). However, we are constrained by the database structure (i.e., the storage of transaction data is segmented by month) and thus obtain monthly data for 8 years instead. Originally, four-month data and annual data were used in Bucklin and Sengupta (1993b) and Stremersch et al. (2007) respectively. To achieve reasonable comparability, we construct the count data for card IDs and terminal IDs in each quarter for the replicating effort. Details of the data summary are included in Table 3 and Table 4 as follows.

Variable	Min	Mean	Max	Correlation with Cumulative Card Diffusion	Variable Description
Cumulative card diffusion	742	2,127,615	4,802,464	1	Active contactless card users in the current quarter
Cumulative terminal diffusion	26	25,548	54,362	0.9961	Active contactless terminal users in the current quarter

Incremental terminal usage	0	1,658	4,701	0.1898	Incremental number of contactless terminal users in the current quarter

Table 3 Quarterly Data Summary, number of observations = 33

Variable	Min	Mean	Max	Variable description
Card usage influx	189	270,369	612,679	New contactless card users in the current month compared with the users in the last three months
Card usage outflow	0	226,509	610,550	Contactless card dropouts in the current month compared with the user base in the last three months
Card usage	189	1,472,045	3,428,438	Active contactless card users in the current month
Terminal usage influx	0	1371	3764	New contactless terminal users in the current month compared with the users in the last three months
Terminal usage outflow	0	880	3595	Contactless terminal dropouts in the current month compared with the user base in the last three months
Terminal usage	19	22,534	48,635	Active contactless terminal users in the current month

Table 4 Monthly Data Summary, number of observations = 99

In the following section, we briefly introduce the background, methodology, and model output of each replicated study. A brief discussion concludes each study with comment on whether a full replication is achieved and where lies the discrepancy. The general modelling framework and the mechanism at work are the key focuses. Results of the replication aim to answer the research question regarding the adequacy of existing approaches in modelling the diffusion of co-dependent innovation.

2.4 Replicated work 1 – Bucklin and Sengupta (1993b)

2.4.1 Overview

Rooted in the classic Bass modelling framework and closely following the multi-product growth model proposed by Peterson and Mahajan (1978), Bucklin and Sengupta (1993b) model the co-diffusion process of complementary innovation in a business-to-business context. The authors define the co-diffusion process as the positive interaction between the demands for complementary innovations that have separate adoption tracks. A positive feedback effect identified between the retailers' demand for scanners and manufacturers' demand for Universal Package Code (UPC) supports this conceptualisation. Bucklin and Sengupta (1993b) is the only work emerging from our literature survey that explicitly models the diffusion of two innovations adopted by two distinct adopting groups. Among vast research outputs in the diffusion of innovation, we are not aware of any other work that explicitly examines the innovation diffused co-dependently in a market with different adopting groups. Although the Bucklin and Sengupta (1993b) work is carried out in the business-to-business setting, we are keen to test whether the same mechanism can be used to explain the diffusion within business users (merchant adopting group) and consumer users.

2.4.2 Data and Methodology

This section summarises the methodology employed in Bucklin and Sengupta (1993b) with any adaption implemented in the present replication. One principle of conducting replication with a new data set is that the new data should be of the same or higher quality than the original one (Block & Kuckertz, 2018). The current work meets this requirement. Bucklin and Sengupta (1993) use monthly data on 1) Purchases of the right to use UPC by manufacturers, and 2) Scanners sold to retailers aggregated on a four-month basis. After this wrangling, the study ended up with 39 data points covering 12 years from 1973 to 1985. Our quarterly data also consists of adoption and use information for both merchant and consumer groups, from 2012 to March 2020, with a total of 33 data points, roughly matching the data granularity of the original study.

The proposed model in Bucklin and Sengupta (1993b) is based on a system of equations in the form of linearised Bass model. In addition to parameters that originate from the classic Bass model, accounting for the innovation effect and imitation effect, the authors propose a co-diffusion effect represented by the parameter of the interacting term of the scanner diffusion and UPC diffusion. The linearised Bass model is first applied to the scanner diffusion and UPC diffusion separately, assuming no interacting effect. The results confirm that the data fits the Bass model and therefore the individual model can serve as the baseline for the proposed models with co-diffusion effects. The authors then construct three sets of systems that consist of two one-way effects models (i.e., Scanner → UPC, UPC → Scanner) and a two-way effects model that allows for simultaneous reciprocal interaction.

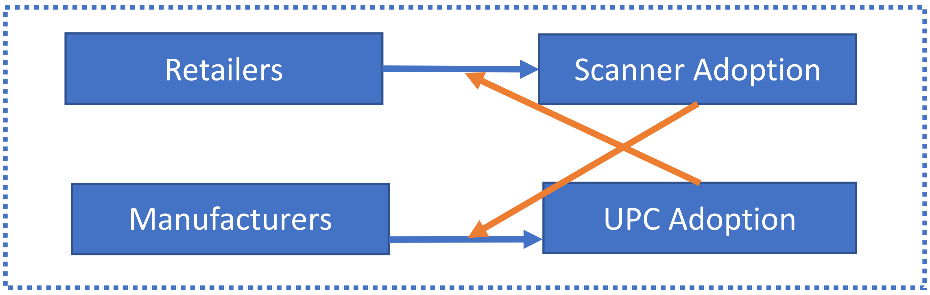


Figure 1 Conceptual Framework of Co-diffusion Effects Modelling[1]

[1] The blue arrows indicate adoption, and the orange arrows represents co-diffusion effects.

2.4.3 Model Specification

Bucklin and Sengupta (1993b) specify two linearised Bass models one with the co-diffusion term to account for the interaction between adopting groups and the other without the interaction. Our replication closely follows this model specification and applies it to payment data. Four types of testing are carried out, namely 1) by applying the independent models to card diffusion and terminal diffusion separately, 2) & 3) by combining each independent model with one interaction model to form one-way effect testing and 4) by applying interaction models to card diffusion and terminal diffusion jointly. We operationalise the diffusion of cards and that of terminals based on the count of distinct innovation usage per quarter, as the proxy of the sales data used in the original study. The following equations specify the models for cards.

Independent Model:

$$Cum\_card_t = a_i + (b_i - a_i + 1)Cum\_card_{t-1} - b_i Cum\_card_{t-1}^2 \qquad \text{(Eq1)}$$

$$Cum\_terminal_t = a_j + \left(b_j - a_j + 1\right) Cum\_terminal_{t-1} - b_j Cum\_terminal_{t-1}^2 \qquad \text{(Eq2)}$$

Interaction Model: Adding the opposite side lag (t-1) and a term capturing the interaction between the same side and opposite-side lags (t-1).

$$Cum\_card_t = a_i + (b_i - a_i + 1)Cum\_card_{t-1} - b_i Cum\_card_{t-1}^2 + c_i Cum\_terminal_{t-1} + c_i Cum\_card_{t-1} * Cum\_terminal_{t-1} \qquad \text{(Eq3)}$$

$$Cum\_terminal_t = a_j + \left(b_j - a_j + 1\right)Cum\_terminal_{t-1} - b_j Cum\_terminal_{t-1}^2 + c_j Cum\_terminal_{t-1} + c_j Cum\_card_{t-1} * Cum\_terminal_{t-1} \qquad \text{(Eq4)}$$

The two-way interaction model is built with both equations from the “interaction model” category.

Details of variable description are listed in Table 5. Figure 2 demonstrates the cumulative growth of cards and terminals over the 33 quarters under study. The up-trending plot shows a rough “S” shape, which may imply the potential for modelling growth with Bass model.

Variable	Notation	Operational measure
Cumulative card diffusion	Cum_card_t	Count of distinct cards used in contactless payment in quarter t, divided by a constant of 8,528,916 to obtain the card penetration level
Cumulative terminal diffusion	$Cum\_terminal_t$	Count of distinct terminals accepting contactless payment in quarter t, divided by a constant of 111,639 to obtain the terminal penetration level

Coefficient of innovation	$a_{i,j}$	Willingness to adopt due to external influence
Coefficient of imitation	$b_{i,j}$	Willingness to adopt due to social influence
Coefficient of co-diffusion	$c_{i,j}$	Interactive effect between the diffusion of cards and terminals

Table 5 Variable Description

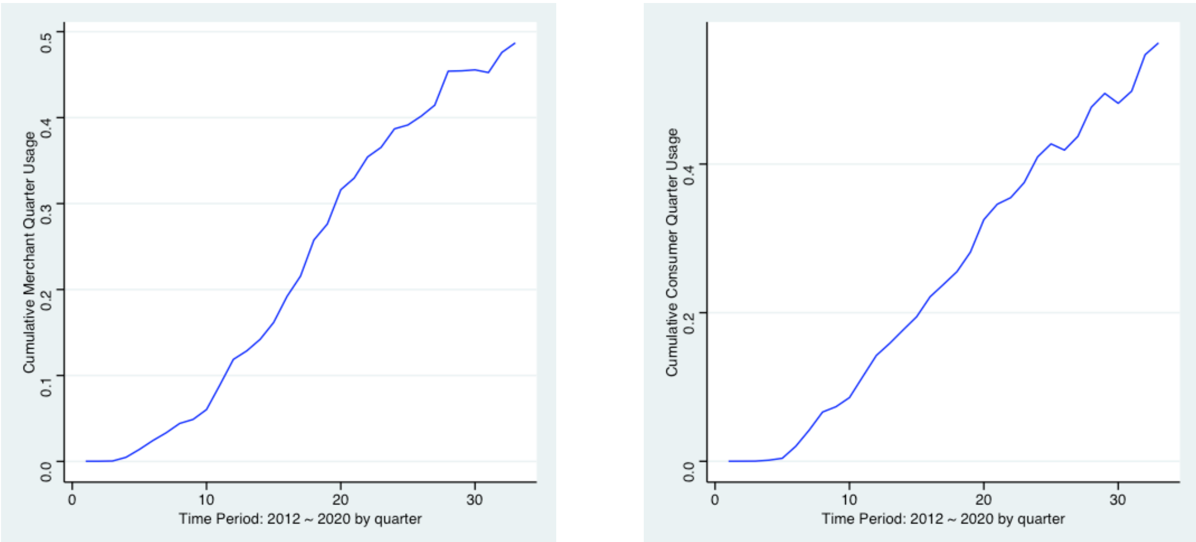


Figure 2 Cumulative Diffusion Plots

2.4.4 Empirical Results

The independent models are estimated with Non-linear Least Square (NLS) approach in R and the system of equations with interaction models are estimated with Seeming Unrelated Regression (SUR). The above estimation approaches are consistent with the replicated study.

Modelling results are presented in Table 6. It is evident that the independent model well depicts the diffusion of cards within the consumer group and the diffusion of terminals within merchant group, demonstrating the robustness and fitness of the Bass model. As with most diffusion studies reviewed in the Chandrasekaran & Tellis (2015), imitation effects dominate the diffusion process of terminals and cards. The ratio between imitation effect and innovation effect (i.e., b/a) is larger in card diffusion than that in terminal diffusion, indicating stronger word-of-mouth impact among consumers than among merchants. The independent models also demonstrate reasonably good model fit, given the high correlation coefficient between predicted and actual values.

Contrary to the results for the Bass model with assumed independent innovation, for the Bass models with one-way interaction only the coefficient of innovation (i.e., a) proves to be significantly different from zero. The coefficient of co-diffusion (i.e., *c*) exerts no significant impact on the diffusion outcome. We provide rationale for this mismatch with the original study in the following section.

Replication Results – Independent					
Cumulative terminal diffusion		Estimate	Std. Error	t value	Pr(>|t|)
	a	0. 011859	0. 003715	3. 192	0. 0033 ***[2]
	b	0. 043180	0. 017275	2. 500	0. 0181 **
MAD	0.2882	MSE	0.0002449	Correlation Coefficient	0.9967
Replication Results – Independent					
Cumulative card diffusion		Estimate	Std. Error	t value	Pr(>|t|)
	a	0. 011455	0. 004274	2. 680	0. 01184 **
	b	0. 060012	0. 018876	3. 179	0. 00342 ***
MAD	0.2689	MSE	0.0002891	Correlation Coefficient	0.9961

Replication Results – One-way Interaction					
Card diffusion impacts Terminal diffusion		Estimate	Std. Error	t value	Pr(>|t|)
	a	0.012834	0. 004345	2. 954	0. 00629***
	b	0.005858	0. 194843	0. 030	0. 97623
	c	0. 031786	0. 186036	0. 171	0. 86556
Replication Results – One-way Interaction					
Terminal diffusion impacts Card diffusion		Estimate	Std. Error	t value	Pr(>|t|)
	a	0.012423	0. 004652	2.671	0.0125 **
	b	0. 138536	0. 177888	-0.779	0. 4426
	c	-0. 088494	0. 189242	-0.468	0. 6437

Table 6 Empirical Summary of Replication against Bucklin and Sengupta (1993b)

Note: the two-way modelling results are not reported given the estimation fails to find convergent results after 50,000 iterations.

2.4.5 Discussion

As shown above, the classic Bass model without co-diffusion effects fits payment data well. Reasonable parameter estimates and sound model fit are found with the Bass model for independent innovation diffusion within the two adopting groups. However, the system of nonlinear equations fails to depict the interaction between adopting groups with payment data, evidenced by the insignificant results from the one-way and two-way models. The attempt to include a co-diffusion coefficient (i.e., c) leads to overfitting of the interaction model and reduces the statistical validity of the system of equations. We suspect the model proposed in

[2] ** $p < 0.01$; *** $p < 0.001$

Bucklin and Sengupta (1993b) fails to accommodate highly correlated diffusion data. In the case of scanner and UPC diffusion, the diffusion plots of the innovations over time show moderate correlation, whereas in the co-dependent payment innovation context the diffusion plots of the two series illustrate a high correlation as reported in Table 3. Since the proposed interaction model includes a product term of both data series, high multi-collinearity undermines the validity of the parameter estimates. Thus, the presence of high correlation represents a boundary condition for Bucklin and Sengupta's approach to modelling diffusion of complementary innovations.

2.5 Replicated work 2 – Stremersch et al. (2007)

2.5.1 Overview

Stremersch et al. (2007) builds on the idea of indirect network effects, being reciprocal enhancement between a pair of innovations, to propose a flexible time-series model to understand the relationship between software availability and compatible hardware sales. The key focus is to examine the magnitude of indirect network effects and unveil the temporal priority between software availability and hardware installed base. Prior to Stremersch et al. (2007), the empirical work on indirect network externalities is rare and whether the hardware sales will lead and have a positive impact on the software availability is not examined. Therefore, the proposed flexible time-series model contributes to the knowledge of network externalities by not only depicting the interaction between the hardware and software with empirical data, but also explaining the temporal leading and lagging effect. The original results show that the availability of compatible software characterises consumers' demand for the hardware, and the development and launch of software is dependent on the size of the installed base of hardware platforms (Stremersch et al. 2007). As a result, even though the software providers and the hardware manufacturers don't interact directly, their operational decisions are influenced by each other through the consumers' mediation, forming the indirect network effects.

2.5.2 Data and Methodology

Stremersch et al. (2007) examines annual hardware sales, cumulative hardware sales and software availability (sales) data from 9 categories, all shown to follow the hardware-software paradigm in other studies (Gupta et al., 1999). Average prices of hardware in each year are also included as a control variable. Our replication adopts quarterly data of terminal diffusion and card diffusion. As we don't have direct price data for terminals, we exclude this control variable in our modelling. One reason for this removal is that for merchants, the surcharge rate on the contactless payment transaction tends to be consistent over time unless drastic changes in their operating environment. According to the data provider, the rate is negotiated between merchants and their own bank/schema based on the industry and the size of their business. Therefore, the cost information is not available in the payment network system. Another modification we made lies in the use of cumulative card usage instead of incremental card usage to represent "software availability". Availability of the contactless cards and terminals is not constraint in our context, as the contactless function is an add-on feature for all chip cards issued, and card payment has a long history in the studied country. Data confirms that the total number of cards in use in the studied country only exhibits a very minor upward-trending in the given timeframe while the uptake of contactless payment cards shows great growth (illustrated in Figure 3). Hence, merchants are likely to be indifferent to the volume of cards issued per year. Therefore, it is consumers' willingness to adopt that places limitations on the diffusion outcome. Note that these modifications are required for the extension to the payment methods context.

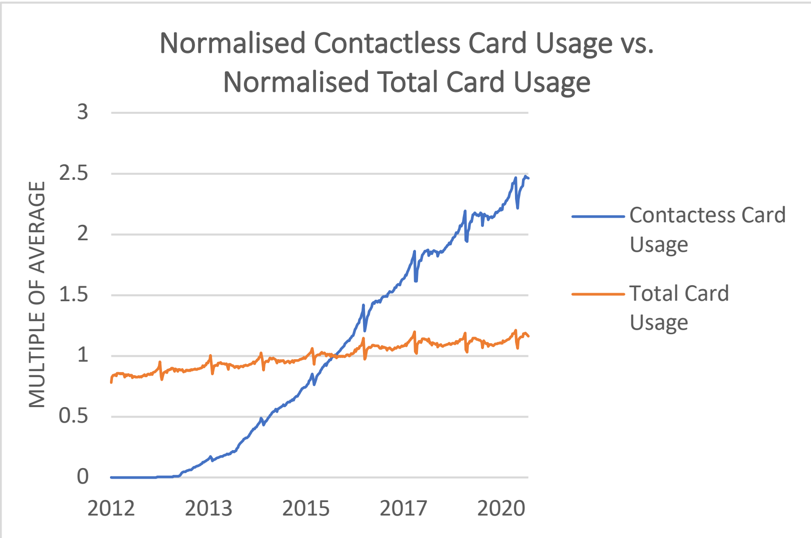


Figure 3 Contactless Card in Use vs. Total Card in Use

The model proposed by Stremersch et al. (2007) is a system of log-transformed equations with lagging effects and time trend factors. This flexible time-series model is estimated with Seemingly Unrelated Regression (SUR). For each category examined, hardware sales are explained by prior hardware sales, average hardware price, and software availability. In turn, software availability is expected to be explained by cumulative hardware sales and prior software availability. The parameters of the key variables are compared as evidence of indirect network effects. Our replication adopts the same model specification, given the slight modification to the variable as mentioned in the prior paragraph.

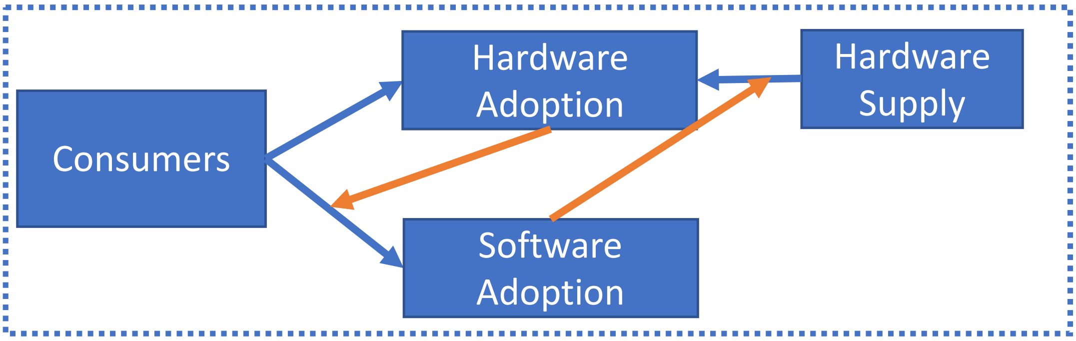


Figure 4 Conceptual Framework of Indirect Network Effect Modelling[3]

2.5.3 Model Specification

The log-transformation is adopted in the original model to account for the non-linear relationships. It is also noted that in the original work, there is asymmetric specification around the cumulative hardware sales (i.e., hardware installation base) and the cumulative software availability (i.e., released software programs). The authors assume the hardware sales in the current period is driven by the hardware installed base and cumulative software availability in the last period. We follow the same approaches here.

$\mathrm{Log}\left(Incr_{terminal_t}\right) = \alpha + \beta * \log(Incr\_terminal_{t-1}) + \gamma * \log(Cum\_card_{t-1}) + \delta * t + \epsilon_t$ (Eq5)

$\mathrm{Log}(Cum\_card_t) = \upsilon + \lambda * \log(Cum\_card_{t-1}) + \eta * \log(Cum\_terminal_{t-1}) + \tau * t + \xi_t$ (Eq6)

Variable	Notation	Operational measurement
Incremental hardware diffusion	$Incr\_terminal_t$	Difference between the count of distinct terminals used in contactless payment in quarter t and the corresponding count in quarter t-1
Cumulative hardware diffusion	$Cum\_terminal_{t-1}$	Count of distinct terminals used in contactless payment in quarter t-1
Cumulative software diffusion	Cum_card_t	Count of distinct cards used in contactless payment in quarter t
Trend variable	t	Time trend, set the first quarter as t =1

Table 7 Variable Description

2.5.4 Empirical Results

The following Table 8 summarises model fitness of the system of equations. The OLS-R^2 shows reasonable model fit for the system of equations, and the McElroy R^2 reported under each equation unveils better model fit for card diffusion (i.e., Adj. R2 = 0.98648) than for incremental terminal diffusion (i.e., Adj. R2 = 0.331316). Detailed parameter estimates associated with corresponding p-values are summarised in Table 9. It is noted that prior cumulative card diffusion significantly encourages the incremental terminal diffusion (0.8691764, $p< 0.01$), and

[3] The blue arrows indicate adoption, and the orange arrows represent indirect network effects.

positively impacts the current level of card diffusion (0. 387902, $p< 0.05$). Therefore, strong same-side and cross-side impacts are established. However, incremental terminal adoption shows no impact on the current level of terminal uptake, indicating the terminal diffusion in each quarter is not impacted by the previous momentum. Our findings are supportive for both directions of cross-side effects.

Replication study – Model Summary						
	N	DF	SSR	detRCov	OLS-R2	McElroy-R2
System	64	56	84.6016	0.163481	0.700829	0.978158

	N	DF	SSR	MSE	RMSE	R2	Adj. R2
Eq5	32	28	82.823	2.957964	1.719873	0.396027	0.331316
Eq6	32	28	1.77862	0.063522	0.252036	0.987789	0.986481

Table 8 Model Summary of Replication on Stremersch et al. (2007)

Replication Results – SUR estimation on Eq5 of Incremental Terminals					
Eq5		Estimate	Std. Error	t value	Pr(>|t|)
	Intercept	-2.326592	2.3522781	-0.98908	0.3310946
	$\log(Incr\_terminal_{t-1})$	0.0446366	0.1937069	0.23043	0.82
	$\log(Cum\_card_{t-1})+$	0.8691764	0.2998015	2.89917	0.0072 **
	t	-0.173647	0.0691219	-2.51218	0.018 *
Number of observations	32	Residual standard error	1.719873	Degrees of Freedom	28
SSR	82.822998	MSE	2.957964	Adjusted R-Squared:	0.33
Replication Results – SUR estimation on Eq6 of Cumulative Cards					
Eq6		Estimate	Std. Error	t value	Pr(>|t|)
	Intercept	3.221391	0.477585	6.74518	2.5265e-07 ***
	$\log(Cum\_card_{t-1})+$	0.387902	0.146759	2.64313	0.0133 *
	$\log(Cum\_terminal_{t-1})$	0.610039	0.179206	3.40413	0.0020 **
	t	-0.017234	0.009238	-1.86555	0.073.
Number of observations	32	Residual standard error	0.252036	Degrees of Freedom	28
SSR	1.778625	MSE	0.063522	Adjusted R-Squared:	0.986481

Table 9 Empirical Summary of Replication on Stremersch et al. (2007)

2.5.5 Discussion

Our findings contradict the original conclusion made in Stremersch et al. (2007) in the following three aspects.

1. Cross-side effects are significant and two-way.

In Stremersch et al. (2007), the authors found weak (i.e., insignificant or negative) evidence of cross-side effects between software supply and hardware demand, and thus suggested that the argument of providing more compatible software in hoping to stimulate hardware demand was not empirically supported. However, applying payment data to the proposed model, we find the cross-side effects are prominent. Not only does the cumulative card diffusion positively impact the cumulative terminal diffusion, the terminal diffusion also positively impacts the card diffusion. This cross-side interaction implies a mutual positive stimulus between consumers and merchants in the process of the co-dependent diffusion. Once consumers succeed in paying with contactless payment method at the merchants' checkout, consumers tend to continue paying with the accepted method next time and merchants will continue accepting this method.

2. Same-side effects are found on the consumer side.

Unlike findings in Stremersch et al. (2007) where the same-side effects mainly reside on the hardware-side, which in the payment context is equivalent to the terminal diffusion, we find significant same-side effects within both terminal diffusion and the card diffusion as well. The finding implies that consumers also play an active role in promoting contactless payment usage as their impacts are found both on the merchants' usage and peer consumers' usage.

3. Existence of two-way network effects.

Stremersch et al. (2007) conclude that the indirect network effect is not pervasive and that most indirect network effects show in one direction only, i.e., hardware stimulates software only, given the investigation of nine consumer electronics industries. Our results, however, reveal that indirect network effects stem both from hardware to software and the other way around in the payment method context. The underlying reason could be that the complementary nature of contactless cards and contactless-enabled terminals solicit more one-on-one interaction than hardware and software which are sold separately with distinct features, such as the prices and genres observed in the consumer electronics categories. In addition, as the payment data is derived from usage cases instead of sales data for programs available in the catalogue, the replication study could potentially capture the interaction better. Each interaction activity could contribute to the usage, which is not necessarily the case when using hardware sales and software supply as indicators for diffusion in consumer market. Therefore, the absence of the co-existence of two-way indirect effects in the original study may be due to the lack of usage data for analysing consumer electronic products.

2.6 Replicated work 3 – Hinz et al. (2020)

2.6.1 Overview

Unlike network effect studies that build on a common assumption of the significant mediating role of consumers to facilitate diffusions of hardware and software, studies in two-sided markets need to account for the interactions between the key decision groups on both sides of the market explicitly. Hinz et al. (2020) examine network effects in a two-sided market by investigating the influx and outflow of participants in an online auction platform on both selling side and buying side. Specifically, the authors state their goal as to investigate the conditions under which the estimation of same-side and cross-side network effects should distinguish between its impact on the number of new customers (i.e., acquisition) and existing customers (i.e., retention). Participants can leave the market as the result of unsatisfactory experience or pressure from competition (Hinz et al. 2020). Only the active participants staying with the platform can spread positive/negative word-of-mouth to both participants and non-participants. The authors propose a new influx-outflow model, which outperformed an existing net-change model as the extant one only shows the resulting impact after cancelling the influence of actual influx and outflow. In the work of Hinz and his colleagues, the main same side effects emerge to be the competitive only, as more participants in the past period tend to decrease the size of participants in the current period. Due to the nature of the online auction platform, more participants on one side will enhance the competition in bidding and thus push the price to disadvantage that side. The main cross side effects are found to be positive between sellers and influx of buyers as well as between buyers and outflow of sellers. That means more sellers from the past will attract more new buyers to participate while more buyers from the past will retain sellers to still be engaged. However, not all participant influxes and outflows are associated with existing participators. The current number of sellers has no impact on the buyers' outflow and the current number of buyers fails to attract more sellers.

2.6.2 Data and Methodology

Hinz et al. (2020) utilise 102,096 transactions completed jointly by buyers and sellers on an online auction platform. The authors estimate the number of active buyers and sellers with a BG/NBD model, a model that informs the likelihood of a customer being active at a given point of time. New customers of the platform, including the influx of buyers and sellers, can be identified in the database. Therefore, by combining the active users and the actual influx users, the number of outflow users is obtainable. As the data is analysed on a weekly basis, a total of 211 weeks of data is fitted into the proposed model. One thing worth noting for the replicated work is the nature of the users' adoption decision towards the platform, where the authors explicitly state the relationship between users and the platform is non-contractual. It is important to point this feature out, as in a two-sided market, users could be bound by contracts such as subscription or membership, so that the size of the adopting groups may not be a true reflection of the interaction between them nor the cumulative adoption outcome on either side. We mimic the replicated work by using monthly data and counting the exact number of active merchants and consumers. As it is derived from transaction information, our data gives us an edge for accurate identification of active users versus churned users, so that in our replication, the step of estimating active users with the BG/NBD model is no longer needed.

The model proposed in Hinz et al. (2020) explicitly accounts for the impact of the influx and outflow of buyers and sellers to understand the growth of users on both sides of the market through same-side and cross-side effects. Therefore, four equations, respectively using influx and outflow of buyers and sellers as outcome variables, are estimated simultaneously using the SUR method. Only one lag is incorporated in the equations, assuming a Markov state applied to the decision of adoption. Our replication study closely matches the model specification.

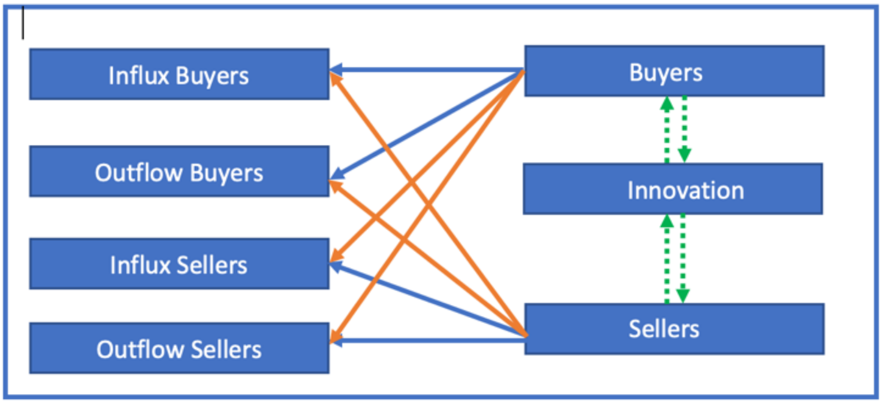


Figure 5 Conceptual Framework of the Effect of Existing Users on Influx and Outflow[4] Users

2.6.3 Model Specification

To study the effect of existing users on the influx and outflow of users on both sides of the market, three pairs of variables, namely the influx, outflow and cumulative diffusion are obtained for both terminals and cards. The six variables are then incorporated into four

[4] The blue arrows indicate same side effects; the orange arrows represent cross-side effects; green dashed arrows represent adoption.

equations, representing the same side and cross side effects on both new uptake and churn. Equations are specified as follows.

$$InfluxCard_t = \delta_1 * Cum\_card_{t-1} + \delta_2 * Cum\_terminal_{t-1} \quad \text{(Eq7)}$$

$$InfluxTerminal_t = \delta_3 * Cum\_card_{t-1} + \delta_4 * Cum\_terminal_{t-1} \quad \text{(Eq8)}$$

$$OutflowCard_t = \delta_5 * Cum\_card_{t-1} + \delta_6 * Cum\_terminal_{t-1} \quad \text{(Eq9)}$$

$$OutflowTerminal_t = \delta_7 * Cum\_card_{t-1} + \delta_8 * Cum\_terminal_{t-1} \quad \text{(Eq10)}$$

Differing from the online platform studied in Hinz et al. (2020), with a small group of users in a larger population, the payment innovation could be adopted by the whole population given its essential functionality. This characteristic of payment innovation makes it hard to obtain brand-new users within a given timeframe. In our replication, we relax the definition of new uptake and determine the new uptake as the newly identified users who have not used the payment innovation in the past three months. Admittedly, this approach cannot rule out returning users who adopted the contactless payment but happened to not use it in the past three months. However, we deem this manipulation as a reasonable proxy for the new users given the computing constraint of determining new users based on 5 million transactional records per day.

Variable	Notation	Operational Measurement
New contactless terminal uptake	$InfluxTerminals_t$	Count of distinct terminals that are newly adopted in the contactless transaction benchmarked against three months before
New contactless card uptake	$InfluxCards_t$	Count of distinct cards that are newly adopted in the contactless transaction benchmarked against three months before
Terminal churn	$OutflowTerminals_t$	$OutflowTerminals_t = Cum\_Terminals_{t-1} - Cum\_Terminals_t + InfluexTerminal_t$
Card churn	$OutflowCards_t$	$OutflowCards_t = Cum\_Card_{t-1} - Cum\_Card_t + InfluexCard_t$
Prior cumulative terminal diffusion	$Cum\_Terminals_{t-1}$	Count of distinct terminals adopting contactless payment in month t-1
Prior cumulative card diffusion	Cum_Cards_{t-1}	Count of distinct cards adopting contactless payment in month t-1

Table 10 Variable Description

2.6.4 Empirical Results

In line with the Hinz et al. (2020) the system of equations uses SUR with Maximum Likelihood Estimation (MLE). The OLS-R^2 shows reasonable model fit of the system of equations, while the model summary for each equation unveils better model fit for card diffusion than terminal diffusion. Specifically, previous card diffusion and terminal diffusion successfully explain the influx and outflow of card uptake with McElroy R-square at 0.87 and 0.75 respectively. However, the explanatory power is reduced in explaining the influx and outflow of terminal uptake with McElroy R-quare of .55 and .16 respectively. We note that the MSE values are high for all equations, which are likely due to the scale of the payment data rather than insufficient explaining power of the model. Note that the replication of Bucklin and Sengupta (1993b) opts for the cumulative percentage as the output and the replication of Stremersch et al. (2007) takes the log transformation in the model specification to reduce the unit. Therefore, compared with the Hinz et al. (2020), the manipulation in the prior two studies leads to to lower MSE and RMSE, but does not necessarily indicate better model fit based on these two metrics.

Replication study – Model Summary						
	N	DF	SSR	detRCov	OLS-R2	McElroy-R2
system	428	416	1.24E+12	1.73E+31	0.811091	0.759395

	N	DF	SSR	MSE	RMSE	R2	Adj. R2
Eq7	107	104	3.63E+11	3492894900	59100.718	0.87604	0.873656
Eq8	107	104	9.10E+07	874930	935.377	0.553641	0.545057
Eq9	107	104	8.72E+11	8387144927	91581.357	0.758569	0.753926
Eq10	107	104	6.83E+08	6566214	2562.462	0.172318	0.156401

Table 11 Model Summary of Replication on Hinz et al. (2020)

Based on the parameter estimates, it is observed that prior level of terminal diffusion discourages new card uptake (-10.67, $p < 0.001$), likely reflecting reduced potential as the pool of non-adopters shrinks. When users adopt contactless cards or terminals, the prior level of terminal diffusion discourages the churn rate (effect of diffusion of terminals on card churn: -37.46, $p < 0.001$; effect of diffusion of terminals on terminal churn: -0.7077, $p < 0.001$;). Although these findings differ from the results in the Hinz et al. (2020), which claim to discover positive cross-side effect but negative same-side effect, our findings are informative in the payment context.

Replication Results – SUR estimation on Eq7 of Influx Card					
InfluxCards ~ Diffusion of Cards and Terminals		Estimate	Std.Error	t	value
	(Intercept)	64589	8844.80	7.3025	p<0.001***
	Cum_Cards_{t-1}	0.2899	0.0391	7.4126	p<0.001***
	$Cum\_Terminals_{t-1}$	-10.6700	2.5094	-4.2519	p<0.001***
Replication Results – SUR estimation on Eq8 of Influx Terminals					

		Estimate	Std. Error	t value	Pr(>|t|)
InfluxTerminals ~ Diffusion of Cards and Terminals					
	(Intercept)	313.22	160.46	1.9521	0.0516*
	Cum_Cards$_{t-1}$	0.0008	0.0007	1.1778	0.2396
	Cum_Terminals$_{t-1}$	-0.0033	0.0455	-0.0730	0.9419
Replication Results – SUR estimation on Eq9 of Outflow Cards					
OutflowCards ~ Diffusion of Cards and Terminals		Estimate	Std. Error	t value	Pr(>|t|)
	(Intercept)	41343	12545	3.2956	0.0011***
	Cum_Cards$_{t-1}$	0.6989	0.0555	12.5993	p<0.001***
	Cum_Terminals$_{t-1}$	-37.4600	3.5593	-10.5245	p<0.001***
Replication Results – SUR estimation on Eq10 of Outflow Terminals					
OutflowTerminals ~ Diffusion of Cards and Terminals		Estimate	Std. Error	t value	Pr(>|t|)
	(Intercept)	-67.3480	355.27	-0.1896	0.8497
	Cum_Cards$_{t-1}$	0.0117	0.0016	7.4400	p<0.001***
	Cum_Terminals$_{t-1}$	-0.7077	0.1008	-7.0212	p<0.001***

Table 12 Empirical Summary of Replication on Hinz et al. (2020)

2.6.5 Discussion

Our replication confirms two out of eight conclusions provided in Hinz et al. (2020), with one being the insignificant cross-side effect between prior card diffusion and new terminal uptake, and the other being the positive same-side competition effect among card diffusion. Specifically, Hinz et al. (2020) utilise the model to prove significant cross-side effects in that existing buyers will attenuate sellers dropout and existing sellers will attract new buyers. As for the same-side effects, the authors' results show strong competitive effects, evidenced by existing buyers discouraging new buyers and existing sellers discouraging new sellers. Our findings, on the contrary, demonstrate positive same-side effect between existing contactless card diffusion and new contactless card uptake while negative cross-side effect between card diffusion and terminal dropout. One potential explanation for the mismatch could be attributed to the nature of the market under study, where users on the same side of an online auction market are set to compete for the limited resources provided on the other side, while payment market does not solicit similar level of competition on the same side.

Although the original results are not fully replicated, the proposed model in Hinz et al. (2020) provides valuable insights for modelling co-dependent innovation such as payment methods. More participants on one side of the market could either lead to fierce competition, as shown in Hinz et al. (2020) or ignite network effects to grow the market faster (as shown in our replication results). Compared with the findings in Hinz et al. (2020) for the same-side and cross-side effects, our results imply more vivid interactions between the participating parties in the two-sided market such as the payment market. There is also the possibility that the interaction shall go beyond one single period lag to allow the impact to develop.

2.7 Conclusion and Implications

Given the gaps in the literature on payment method diffusion, we select three studies with potentially useful modelling framework as the target for replication efforts to explain the growth pattern of payment innovation: Bucklin and Sengupta (1993b) from the diffusion literature, Stremersch et al. (2007) from the area of indirect network effects, and Hinz et al. (2020) examining the interaction between two sides of a platform-based market. We fail to fully replicate prior results.

Although the replication of Stremersch et al. (2007) shows significant effect between the card diffusion and incremental terminal uptake, the theoretical implication differs from the conclusion made in the original work implying weak and asymmetric indirect network effects across 9 industries. Our findings, in contrast, show symmetric cross-side effects between card diffusion and terminal diffusion, albeit a slight modification on the variable representing the availability of software. For the other two studies, the replication results only confirm part of the proposed mechanisms, namely the Bass model without the interaction effect for the card and terminal diffusion in Bucklin and Sengupta (1993b) and part of the same-side negative effect for card diffusion in Hinz et al. (2020).

The replication attempt for Bucklin and Sengupta (1993b) demonstrates the robustness of the Bass modelling approach in accounting for the diffusion of payment innovation in each group separately, whereas the interaction between the two adopting groups in the diffusion process fails to be sufficiently explained. A better approach is needed to depict the interaction between the adopting groups while accommodating the potential high correlation between the diffusion outcome of co-dependent innovation. Therefore, a system of equations with linearised format may avoid multi-collinearity compared with building interaction terms via the product of individual diffusion outcome.

Results from the replication of Stremersch et al. (2007) provide insights on the nonlinear growth features and the two-way interdependency between the involved innovations, as a system of equations is an ideal approach for simultaneously estimating the diffusion within multiple adopting groups. However, the context of consumer market does not exhibit significant indirect network effects since the interactions between the hardware manufacturers and software developers are mediated by consumers' purchase decisions. Modelling co-dependent innovation therefore needs to account for the distinct adoption decisions and the direct reactions of each adopting group, which is a key component missing in the Stremersch et al. (2007) work.

Although the replication results fail to replicate the findings in Hinz et al. (2020), it is undeniable that the proposed approach sheds light on the understanding of participants on both sides of the market. Differentiating influx and outflow adopters can be useful, especially in the early diffusion stage when the user base could change drastically, and the approach allows for lagged interactions between the adopting groups. Only by differentiating the impacts of previous diffusion level on the influx and outflow shall we be able to discover the interesting impact of terminal diffusion on preventing churn on both sides of the market. However, as merchants usually take time to react to the market, it would also be useful to test more lags in the modelling structure and examine whether merchants can also show encouraging effect on diffusion in relatively long term.

2.8 Contribution

We contribute to knowledge of payment method diffusion by testing modelling frameworks for the diffusion of co-dependent innovation. The co-dependency between the innovation and the adopting groups implies that innovations evolve as a result of the interaction between the adopting groups. This co-dependency idea is increasingly important in modern society, as the society calls for cooperation and involvement (Gruber, 2020). However, the diffusion of this type of innovation has yet to be studied and the modelling practices explicitly designed for co-dependent innovation are scant. The current study attempts to fill this knowledge gap by defining co-dependent innovation and proposing relevant approaches for modelling the diffusion of co-dependent innovation based on similar mechanisms identified in prior research for similar markets as the starting point. The current work contributes to the theoretical advance in innovation categorization and thus lays the foundation for more research on co-dependent innovation from all aspects.

Although we fail to fully replicate each prior study, the replication efforts offer insights and limitations in modelling co-dependent innovation in a payment method context. We find the Bass modelling approach describes diffusion within individual adopting groups well, but the co-diffusion design in Bucklin and Sengupta (1993b) fails to identify interaction effects between adopting groups due to collinearity. The system of equations approach in Stremersch et al. (2007) shows the ability to identify cross-effects but is theoretically unsatisfying as the hardware-software paradigm involves consumers as independent mediators between the adopting groups, unlike payment methods where consumers are one of the adopting groups. The approach of Hinz et al. (2020) is theoretically more satisfying in the payment methods context than that of Stremersch et al. (2007), and allows for the identification of cross-effects, but is restricted to one-period lag, which may not be realistic in the context of payment method diffusion. Further, it may be overreaching to simplify the interaction between adopting groups as the network effects or co-diffusion effects.

Given the partial replication of the empirical results of all selected work, our replication efforts highlight the importance of promoting modelling practices that specify the boundaries and limitations of the model application. The boundary for any proposed models in any field is strengthened with replication efforts, including a robustness test as an integral part of the study or formal replication with different data contexts and time spans (Mueller-Langer et al., 2019). Newly proposed models are expected to demonstrate reproducibility to be acknowledged as a scientific method (Kerr et al., 2016). Otherwise, they are merely modelling approaches for understanding questions in specific circumstances.

Last but not least, our replication work contributes to the payment modelling practice by testing three potential mechanisms with eight years of payment method usage data. Quantitative modelling is less common than the qualitative approach (i.e., Kim, Mirusmonov, and Lee 2010; Liébana-Cabanillas, Molinillo, and Ruiz-Montañez 2019; Wang and Lin 2019) in prior payment method studies, likely due to the lack of availability of payment transaction data. Therefore, empowered by the transaction data from a leading payment service provider, the current work evaluates the generalizability of the chosen models to the payment innovation diffusion. Our replication results point us in fruitful directions of adapting the models to meet the modelling needs, such as to leverage the system of equations approach and to incorporate multiple lag structures.

In sum, the failure of replicating the empirical results of the selected work, and the theoretical limitations highlighted by the replication efforts, unveil the pressing need to build a tailored model to examine the co-dependent diffusion of innovation. Although the mechanisms proposed in prior work fail to fully explain the diffusion process of co-dependent innovation taken up by more than one adopting groups, our results shed light on how a modification of the proposed mechanism could be helpful in serving the purpose. Key priorities for investigation include combining approaches used in prior research, such as relaxing the assumptions of no-dropout (outflow) in the Bass modelling approach and/or relaxing the assumption of one-period lags in estimating cross-effects.

Appendix A Statement of Contribution

DRC 16

MASSEY UNIVERSITY
TE KUNENGA KI PŪREHUROA
UNIVERSITY OF NEW ZEALAND

GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Xing (Alison) Chen
Name/title of Primary Supervisor:	Prof. Malcolm J. Wright
In which chapter is the manuscript /published work:	Chapter 2

Please select one of the following three options:

- ○ The manuscript/published work is published or in press
  - Please provide the full reference of the Research Output:
- ○ The manuscript is currently under review for publication – please indicate:
  - The name of the journal:
  - The percentage of the manuscript/published work that was contributed by the candidate: 60.00
  - Describe the contribution that the candidate has made to the manuscript/published work:

    The candidate completed the research design, literature review, model specification, analysis and writing. The role of the supervisors has been restricted to assisting with the conceptualisation of the project, advisory comments on research design and analysis, and critical evaluation and editorial comments on written drafts.
- ● It is intended that the manuscript will be published, but it has not yet been submitted to a journal

Candidate's Signature:	Xing Chen Digitally signed by Xing Chen Date: 2022.09.17 23:31:31 +12'00'
Date:	17-Sep-2022
Primary Supervisor's Signature:	Wright, Malcolm Digitally signed by Wright, Malcolm Date: 2022.09.18 11:38:42 +12'00'
Date:	18-Sep-2022

This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis.

GRS Version 5 – 13 December 2019
DRC 19/09/10

[redacted]

Chapter 3 The Diffusion of Co-dependent Services

Abstract

Co-dependent diffusion describes the uptake of innovations for which the base functionality is contingent on the joint uptake of related innovations across two (or more) populations and thus requires diffusion among each of them. For instance, the diffusion of a contactless payment system is co-dependent as it requires joint uptake of card payment from consumers and contactless terminals from merchants. To date, the innovation literature does not inform about the driving forces and temporal pattern of co-dependent diffusion. To fill this gap, the authors apply the Bass model with the churn rate proposed in Libai et al. (2009) to eight years of transaction-based usage data of an innovative payment method. Results confirm that the Bass framework captures core aspects of co-dependent diffusion, accurately modelling the diffusion across the two adopting groups. The results also show the usefulness of churn rates as a proxy for feedback effects in co-dependency, as their absence leads to underestimates of growth potential. Simulation results show that as churn rates increase, the size of the imitation effect increases while that of the innovation effect decreases, demonstrating how co-dependency is impacted within this modelling framework. The insights from the current work suggest that the diffusion of co-dependent service innovation differs between the adopting groups. Thus, service providers should tailor their strategies toward each group to promote diffusion, with the consideration of the respective churn rates.

Keywords:

Diffusion modelling, co-dependent innovation, churn rate, merchant adoption, payment methods

3.1 Introduction

Unlike traditional innovations in consumer durables categories, which function alone once adopted, a growing number of technology innovations rely on the co-working of more than one product or service. These innovations require interaction between the adopting groups for successful diffusion. Examples include contactless payment cards and contactless point of sale (POS) terminals, as well as electric vehicles and charging stations. We coin the term co-dependent innovation to describe innovations that require joint uptake by more than one group to enable functionality.

Prior research incorporates dedicated modelling approaches to deal with related innovations, such as complementary innovations (i.e., Bucklin & Sengupta, 1993b; Cenamor et al., 2013; Clements & Ohashi, 2005; Gagliardi et al., 2018), contingent innovations (i.e., Bayus, 1987) and substitute innovations (i.e., Adner & Kapoor, 2016; Chandrasekaran et al., 2022; Norton & Bass 1987). The applications in these studies include the PC and internet (Dewan et al., 2010), CD players and CD titles (Basu et al., 2003) as well as game consoles and game titles (Binken & Stremersch, 2009; Stremersch et al., 2007). However, all these applications, mainly in the consumer durables category, involve related innovations adopted by the same group (e.g., consumers). None of the prior studies accounts for the success of innovations that relies on different adopting groups, a critical requirement of co-dependent diffusion, which is itself an emerging feature of technological innovations in service industry. It remains unknown how co-dependent innovation diffuses or how best to describe co-dependency. The current study, therefore, sets out to clearly define co-dependent diffusion, identify a candidate mechanism for modelling feedback effects between the two adopting groups, and provide substantive evidence on the patterns of diffusion for the studied innovation.

We address the questions raised above in a formal manner as:

RQ1: What are the driving forces of the diffusion of the co-dependent innovation for each adopting group?

RQ2: Can the chosen approach detect feedback effects between these co-dependent groups?

RQ3: Are these findings robust across different industries?

As prior modelling frameworks for related innovations and platform-based markets fail to explain the co-dependent diffusion of innovation (evidenced in Chapter 2), we resort to a different diffusion model specification, dedicated to service innovation, to attempt to account for co-dependency. We adopt the model proposed in Libai et al. (2009) that extends the Bass modelling framework (Bass, 1969) by incorporating churn rates to account for dissatisfaction from adopting units leading to discontinued usage. Churn rates were initially examined in the management literature to measure the portion of customer dropout each period (Kumar & Reinartz, 2012). Libai and colleagues believe that users of service innovations are likely to return instead of dis-adopting for good, once the service is improved or the facilitating factors are changed. Therefore, in essence, the churn rates describe the outcome of the interaction between users and providers and capture the effects of discontinuance by either group due to post-usage dissatisfaction. In the co-dependent diffusion context, we test the churn rates as a proxy for the feedback effect between adopting groups.

The current study applies the service diffusion model to usage data of contactless payment methods involving consumers and merchants in a developed western country. The contactless payment innovation, introduced to the country in late 2011, qualifies as co-dependent service, with its diffusion requiring consumers' willingness to use and merchants' willingness to accept to jointly enable the payment transactions to take place. The data provider possesses 70% of the payment market share, and the data set we leverage consists of the transaction data of the studied contactless payment methods. We derive the churn rates based on real data. In addition, we simulate churn rates to gain insights on how the path of diffusion would change as the churn rate changes.

Results confirm that the service diffusion model can depict the co-dependent diffusion of innovation once the churn rates are adequately accounted for. The model fits well with the diffusion of both adopting groups and demonstrates that the diffusion paths of contactless payment innovation differ between consumers and merchants. Merchants tend to have a higher imitation effect, likely resulting from peer pressure, while consumers exhibit a greater innovation effect as the result of advertising and individual innovativeness. Zooming in on the churn rates, the simulations show that the churn rate drives the innovation effect and imitation effect in opposite directions as well as varying between consumers and merchants. The different churn rates imply that the feedback effects between consumer and merchant adoption are asymmetric.

Our contribution to the diffusion literature is threefold. First, we pioneer in examining the diffusion of co-dependent service innovations with the Bass modelling approach and demonstrate the feasibility of applying the service diffusion model to the co-dependent diffusion of innovation. Given the co-dependency between the adopting groups, the diffusion paths could differ as per each adopting group's initial intention and subsequential reaction to the diffusion level of the other group. We leverage the diffusion of service modelling framework proposed by Libai et al. (2009) to depict this co-dependency using the respective churn rates as a proxy. The results confirm this model choice by showing sound model fit for the diffusion among merchants and consumers and presenting distinct diffusion characteristics for each adopting group. Merchants are featured with a higher churn rate and show more significant imitation effects that drive the diffusion, while consumers have a lower churn rate but higher innovation effects.

Second, we explicitly account for the diffusion of innovation on the merchant side, which complements most diffusion studies focusing on the consumers' uptake of complementary or contingent innovation (Clements & Ohashi, 2005; Laukkanen, 2016; Mallat, 2007; Wu & Chu, 2010). As co-dependent innovations, such as payment method innovation, rely on the joint efforts of consumers and merchants to diffuse, the diffusion outcome of merchants is also critical. Our attention to the merchant side thus expands the knowledge of innovation diffusion, enabling innovation facilitators to leverage such knowledge for better diffusion outcomes. As part of the robustness testing, we also report the diffusion outcome across key industries for merchants and present the general consistency in diffusion patterns. However, it is worth noting that deviation is found for a small selection of industries, where the industrial uptake of the innovation is later than their peers while the associated churn rates are higher than peers. If greater imitation effects are believed to be the manifestation of the high popularity of the innovation among users, the co-existence of high churn rates and high imitation effects during the growth stage after the introduction for some industries, such as automobile and transportation, conflicts with this common wisdom.

A third contribution relates to the utilisation of churn rates as a proxy of the feedback effects between the adopting groups. The diffusion of service innovation can incur churning due to temporary dissatisfaction emerging from poor service quality or inconvenience, leading to service discontinuance (Libai et al., 2009). By applying the service diffusion model to the co-dependent innovation context, we acknowledge the churn rate and use it to capture the dynamics between the adopting groups. The churn rates also vary between the two adopting groups, implying potential asymmetric feedback effects worth further exploring.

The study proceeds as follows. In the next section, we give an overview of the three streams of literature that inform our study. Following this, we introduce the study framework and hypothesis to guide the empirical work. A brief introduction is given to the empirical study context – the contactless payment market in a developed western economy – with a description of the key data and measurement. To facilitate the understanding of merchant uptake in the diffusion process of contactless payment, we compare the diffusion parameters of merchants against that of consumers and further examine the industry-specific merchant parameters and the impact of simulated churn rates on merchant adoption. To conclude the study, we discuss the findings for theoretical and managerial implications. Limitations and future research directions are laid out in the end.

3.2 Relevant literature

3.2.1 Diffusion of Complementary Innovation

In the seminal work on the diffusion of innovation, Rogers (2003) introduces the idea of technology clusters, which in essence, describes the interrelationship between innovations that can either be directly assessed by related functionalities they each provide or by the interrelated behaviours of users. Functionally related innovations could boost the sales of each other since the adopting unit can benefit from the combined functionalities offered by the related innovations. Innovations that are not seemingly related can also see sales enhancement if the innovations answer to similar consumer behaviour. For example, research shows that recycling behaviours are related to energy conservativeness and therefore people who recycle newspapers and cans are more likely to install solar panels (Leonard-Barton, 1981).

Marketing studies mainly examine the technology clusters based on related functionalities. A handful of studies further distinguish technology clusters based on how one product is directly related to the other. Contingent products refer to the situation where purchasing a secondary product is contingent on purchasing a primary product (Bayus, 1987). There is an implied sequence of purchases where the contingent decision of the second purchase is based on the decision of the primary purchase (Rogers, 2003). In a similar vein, video game titles and game consoles, CDs and CD players can all be viewed as pairs of contingent products. Complementary products, sometimes used interchangeably with contingent products, refer to a similar situation in that products shall be bought and consumed together to achieve the full utility (Meyer & Winebrake, 2009). The complementarity arises between the products to form a system, which allows the interaction between the products and implies no strict sequence of obtaining the secondary after the primary (Chen & Liu, 2005; Katz & Shapiro, 1994). Based on its definition, the complementary category encompasses the class of contingent products and broadly categorises all products used together to enable full functionalities.

In the examination of complementary innovation, indirect network effects are extensively discussed in both conceptual and empirical studies, covering compatibility as well as demand and supply effects for complementary products (Basu et al., 2003; Binken & Stremersch, 2009; Knittel & Stango, 2004). The hardware-software paradigm, which is by nature a complementary pair, is deemed a suitable context for examining indirect network effects and is thus extensively researched. Indirect network effects are identified between the demand for the hardware and the software supply, as the increased availability of software stimulates consumers' demand for the hardware (Gupta et al., 1999). Since the hardware manufacturers cannot directly influence the software providers, consumers are the key agents in the market who buy from both sides and thus mediate the interaction between the two sides. Stremersch et al. (2007) examine the indirect network effects across nine consumer electronics markets with corroborative findings. In general, hardware sales precede software availability growth, and the increased availability of software positively impacts the sales of compatible hardware. Apart from the quantitative availability of software, the effects of software quality and the multihoming features of the software are also examined under the framework of the indirect network effect (Binken & Stremersch, 2009; Landsman & Stremersch, 2011). Multihoming indicates the expanded compatibility of hardware that results in more significant software growth beyond the original specialised functional match.

The co-diffusion process of complementary offerings proposed in Bucklin & Sengupta (1993b) does not rely on consumers' mediation. Instead, a positive interaction or feedback is identified between the two groups of end-users, serving as a piece of supportive evidence of an alliance between the manufacturers of complementary products (Bucklin & Sengupta, 1993a). In another example, Lee et al. (2019) build on the technology adoption model (TAM) (Davis, 1989) to explore mobile payment adoption from the perspectives of both consumers and merchants. The authors propose an integrated adoption model that examines the reciprocal relationship between consumer adoption and merchant acceptance. Results confirm the existence of network externalities with the respective adoption model and quantify the magnitude of the externalities with the integrated model.

Despite the significant research efforts spent in understanding the diffusion of complementary innovation, there is limited understanding of whether the knowledge can be directly applied to the diffusion of co-dependent service innovation. On the one hand, co-dependent innovation differs from complementary innovation in terms of the requirement of co-dependency between more than one adopting group to enable the innovation simultaneously. On the other hand, existing work on the indirect network effects and the co-diffusion in a business-to-business or consumer product setting may seem relevant for co-dependent innovation of consumer services. Yet it is unknown whether the identified interaction effects play a role in the service diffusion context. Therefore, Peres et al. (2010) urged to gain more understanding of how service innovation diffuses in the modern world. Our current study attempts to answer this call.

3.2.2 Diffusion of Services

Although service innovation has played an increasingly important role in the global economy, compared with the extensive research on the diffusion of consumer durables and electronics, research on the diffusion of services and technologies remains scant (Zhang Foutz & Rao, 2018). Libai et al. (2009) provide one pioneering piece of work, if not the only one, that examines the effect of customer disadoption and customer churn for service firms. A distinguishing feature between services and products lies in the different utilities generated from the repeated usage of the products versus services. Repetitive usage forms a critical part of the revenue stream of service, while the initial purchase is the main contributor to product success. Libai et al. (2009) point out in their service diffusion study that the growth of repeated purchases is a critical source of the service providers' revenue. Therefore, post-adoption usage behaviour determines the commercial success of service-related innovation, differentiating its role in consumer goods diffusion. However, most of the diffusion research in the service domain still models the growth of the services in the same ways as it does for consumer durables.

Noticeably, the rise of the sharing economy boosts service innovation. Studies on the adoption of house sharing, i.e., Airbnb, and shared mobility, i.e., Uber, Didi, investigate the growth of the new services and their impact on traditional industries (Chen & Wang, 2019; Zervas et al., 2017; Zhang et al., 2020). In the shared mobility study, Zhang et al. (2020) elaborate on a two-stage usage-adaption process of the diffusion of carsharing innovation. As carsharing service is operated in regional areas, the initial adoption may be contingent on the information flow – only those who possess the information about the carsharing stations in their local area are in the position to make an adoption decision. Therefore, the initial adoption peak could result from the information bottleneck instead of market saturation. The authors further argue that continued usage determines the market potential only in the later stage. Due to data constraints, their empirical work focuses only on the first stage of initial adoption and leaves the second stage of long-term usage untapped.

3.2.3 Diffusion of Innovation in Business-to-Business Context

The diffusion of service innovation in a business setting mainly gains research attention in the information system area. In the business-to-business context, technology adoption studies draw on the expectation-confirmation theory (Davis et al., 1989; Venkatesh et al., 2003) and take the perspective of drivers of individual adoption instead of the aggregate level of diffusion among the population.

Technology adoption in the business-to-business context relies on factors that differ from consumer adoption, such as various perceptions used as the proxy for expectation. Examples of driving factors of adoption include organizational structure characteristics and organizational performance (Greenhalgh et al., 2004; Oliveira & Martin, 2011; Wolfe, 1994). The theory then links the adoption outcome back to expectations to form an evaluation based on business considerations (Kim & Malhotra, 2005).

In the marketing literature, although merchants are significant players in purchasing activities, the focus of innovation diffusion is tightly centred around the consumer group. One exception is Bucklin & Sengupta (1993b), whose seminal work examined the joint diffusion of the Universal Package Code (UPC) symbol and the retail scanners in a business context. Another is Plouffe et al. (2001), who compared consumer adoption and merchant adoption towards a smart card system and concluded various characteristics of the adopting groups that stimulate adoption. But again, this is merely adoption, not comprehensive knowledge of how co-dependent innovation would diffuse over time.

We summarise the literature from the aforementioned three streams that closely relate to the current study as follows:

Citation	Innovations	Consumer Adopters	Merchants Adopters	Diffusion Over Time	Merchant Differentiator	Key Insights
Bucklin & Sengupta, 1993b	Industrial innovation (Universal Package Code (UPC) symbol and scanner)		✓	✓	By size	Study the diffusion of complementary innovations with a constant co-diffusion effect.
Stremersch et al., 2007	Consumer electronics (Hardware and compatible software)	✓		✓	NA	Demonstrate the effect of cumulative hardware sales (diffusion) on software sales(diffusion).
Gupta et al., 1999	Consumer durables (Digital TV and digital programs)	✓		✓	NA	Propose and test consumer response model to forecast market evolution (diffusion).
Bayus, 1987	Consumer electronics (CD player and CD discs)	✓		✓	NA	Forecast sales (diffusion) for contingent products.
Ladrón de Guevara et al., 2007	Consumer electronics (PC and Internet)	✓			NA	Propose a modelling framework for cross-product interactions.
Dewan et al., 2010	Consumer electronics (PC and Internet)	✓		✓	NA	Demonstrate the co-diffusion effects for PC and Internet are prevalent across the globe.
Cenamor et al., 2013	Consumer electronics (Game console and game titles)	✓			NA	Demonstrate the platform adoption is driven by the users of complementary products.
Niculescu & Whang, 2012	Service innovation (Wireless voice and Wireless data)	✓		✓	NA	Demonstrate two-way co-diffusion effects between base users and sophisticated users.
Plouffe et al., (2001)	Service innovation (Smart Card System)	✓	✓		None	Driving factors for consumer adoption and merchant adoption are different.
Au and Kauffman (2008)	Service innovation (Mobile payment)	✓	✓		None	Provide guidance on the technology adoption from an economic perspective.
Current study	Service innovation (Contactless payment methods)	✓	✓	✓	By industries	Demonstrate the impact of churn rates on the diffusion of co-dependent innovation.

Table 13 Literature Summary

Given the summary above, the gap in the literature is evident. Limited research has been done to address the innovation taken up by two distinct groups. No prior work investigates the diffusion of co-dependent service innovation between two adopting groups. Prior knowledge on the diffusion of complementary innovation may not hold given that the innovations being studied are adopted by a single group, i.e., the consumer group, instead of requiring simultaneous usage by a dyad pair. The interactions between the two adopting groups add to the uncertainty of the diffusion process, as the adoption and disadoption (i.e., churn) may influence not only the ongoing decisions of one group alone but also the two groups collectively. Thus, the churn rate in the proposed model may capture the dynamics in the interaction and pose as a proxy for feedback effects from one group to the other.

3.3 Study Framework

The current study examines the diffusion of co-dependent innovation across two adopting groups with a three-stage design. When looking into long-term usage, our literature survey shows that churning has been studied under the customer lifetime value topic as a key obstructor of growing customer value in the long-term (Kumar & Reinartz, 2016). Marketing activities such as free trial promotions help attract customer adoption during the early months since the innovation is introduced, but risk incurring a higher churn rate at the end of the free trial period due to the unsatisfied quality of the innovation (Foubert & Gijsbrechts, 2016). As the diffusion of co-dependent innovation requires the co-working of the two adopting groups to jointly adopt and use the innovation, the level of satisfaction between groups could be a determinant of continual usage. To keep both user groups satisfied, providers of interdependent innovations strive to increase the engagement of each group during each interaction and hence avoid low satisfaction resulting in churn. The impacts of churn rates on the diffusion of service innovation are studied in Libai et al. (2009); however, to our best knowledge, no study has explicitly incorporated the churn rates in the diffusion of co-dependent innovation.

Therefore, as the first step, we compare the Bass modelling with and without a churn rate configuration to establish the diffusion characteristics on the consumer and merchant sides. Then, we dive into the dynamics of churn rates as the proxy for the feedback effect between the dual adopting groups. Lastly, we provide a special check for the diffusion of co-dependent innovation across different industries. We hypothesise that each adopting group impacts the diffusion of the innovation, and the diffusion outcome, in turn, impacts the continual usage decision of each group through the churn rates. Therefore, the churn rate could be more important in the diffusion of co-dependent service innovation than that of independent service innovation. An illustrative study framework is shown below.

As mentioned before, the payment market provides an ideal context for examining co-dependent innovation. The diffusion of payment innovation, such as payment cards and contactless payment methods, constitutes a pair of complementary innovations that requires

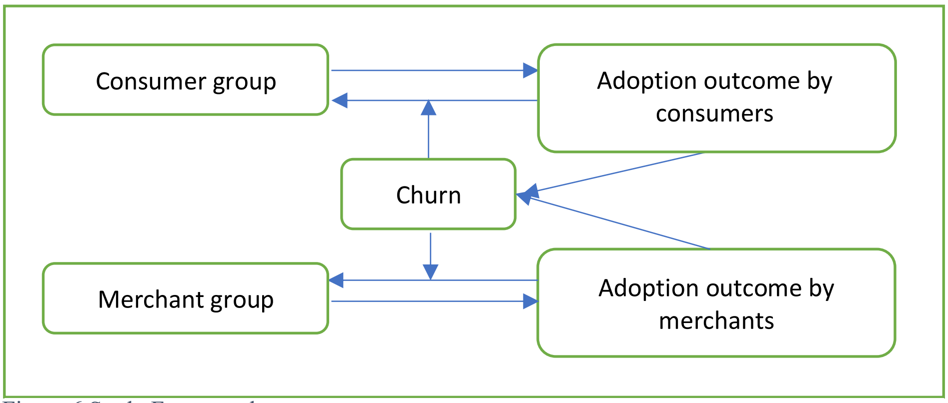


Figure 6 Study Framework

the uptake by two distinct user groups – consumers and merchants. Therefore, our research aims to disentangle the diffusion process to provide an understanding of the role of each adopting group and the interactions between them that collectively impact the diffusion path of contactless payment innovation. Next, we introduce the empirical context and describe the data and measurement for the analysis.

3.4 Empirical Study

3.4.1 Sample

We investigate the diffusion of contactless payment methods using a transaction-based data set containing weekly counts of distinct cards and terminals used in contactless payment transactions. The data provider, who wishes to stay anonymous, operates the payment network in a developed western country with more than 70% of the market share. As contactless payment methods increase payment efficiency by reducing the hassle of inserting a card into the terminal and typing in the PIN to complete the transaction, it is not surprising to see rapid growth associated with them. Since their first introduction into the studied country in late 2011, their usage has accounted for 30% of all transactions by the end of 2020, indicating a 60% compound annual growth rate. The local payment network started to label the payment cards and terminals used in contactless transactions at the beginning of 2012, and since then, the data has been consistently recorded. Therefore, our data accounts for all transactions processed by the provider from 2012 to 2020, accounting for over 70% of the share of non-cash transactions nationwide during the observation period (i.e., payments made by cards, mobile apps, and webpage). The rich data set enables us to investigate the diffusion of contactless payment methods among consumers and merchants and provides ample information for merchants across all key industries.

3.4.2 Measurement

We present the variables and measurement used in the study as follow.

Variable Names	Description	Literature
Card Usage	The count of distinct payment card numbers used in contactless transaction in each period (weekly, bi-weekly, four-weekly). The card numbers represent both physical payment cards and virtual payment cards associated with mobile payment.	Carbó-Valverde et al. (2016)
Term Usage	The count of distinct terminals used in contactless transaction in each period (weekly, bi-weekly, four-weekly).	/
SIC ID	Standard industry classification code that is adopted in the studied country.	Yli-Renko & Janakiraman (2008)

Table 14 Summary of Key Variables

Consumer Usage

We use card usage to represent consumer usage, which is measured by the number of distinct cards used for contactless transactions in the specified time interval (i.e., weekly, bi-weekly, and four-weekly). In line with Wright (2002), we assume that consumers choose a focal mode of payment. One payment study uses card issuance size to represent card adoption (Carbó-Valverde et al., 2016). After reviewing the card issuance data obtained from the public source (i.e., the website of the Reserve Bank of the studied country), we deem this measurement less relevant to the study of contactless payment diffusion. The issuance size could serve as the base for general card adoption but not necessarily relate to the uptake decision regarding a specific card function.

Merchant Usage

We use terminal usage to represent merchant usage, which is measured by the number of distinct terminals accepting contactless transactions in each period. Specifically, we count the number of terminals that have accepted at least one contactless transaction for the specified time interval (i.e., weekly, bi-weekly, and four-weekly). An alternative measurement related to the merchants' uptake of contactless payment is the count of contactless-configured terminals per period. However, after exploring the data based on configuration, we deem this measurement could inflate merchant usage as merchants can refuse to take contactless transactions even with their terminals configured as contactless enabled. Therefore, to avoid potential overrepresentation, we use the count of terminals based on contactless transactions to reflect true contactless payment acceptance corroborated by the evidence of contactless payment transactions.

We show the data range of card usage and terminal usage in the following table. The standard deviation value shows that consumers' usage decision tends to have a greater deviation from its mean value, indicating a more dispersed diffusion outcome than that of merchants.

Variable	Min	1st Quantile	Median	Mean	3rd Quantile	Max	Standard Deviation	Correlation with Card Usage
Card Usage	33	143,729	773,046	893,457	1,645,505	2,220,417	741025.4	1
Terminal Usage	12	4,153	17,068	19,600	34,858	42,683	15160.34	0.9951

Table 15 Summary of Card Usage and Terminal Usage

Standard Industry Code

Standard Industry Code (SIC) stored in our data provider's database is formatted based on the industry coding standard adopted in the studied region. It categorises merchants into the industry classification based on their primary business. The database contains 218 unique SIC IDs. Consolidating subcategories into the main industry types initially yielded ten industries. We decided to list "Restaurant and Café" as a stand-alone category as the demand for payment innovation could be unique for restaurants and cafés compared with other subcategories classified in "Entertainment and Hospitality". SIC classifies restaurants and cafés under "Entertainment and Hospitality", a category also includes hotels, motels, night clubs among others. Allowing "Restaurant and Café" to sit within the "Entertainment and Hospitality" category tends to obscure the contactless payment innovation growth in restaurants and cafes, whose market penetration appears to be greater than other sub-categories, and thus fails to identify interesting details across industries (merchants). In addition, payment network facilitators are interested in merchants running restaurants and cafés, who are believed to have greater enthusiasm to accept contactless payment and to benefit from fast checkout, albeit the extra surcharges. Therefore, grouping "Restaurant and Café" separately provides more interesting managerial implications. We set out our examination of the diffusion of contactless payment methods in 11 industries.

As the diffusion process is time-dependent, industries that introduced the innovation at a relatively late stage may enjoy rapid diffusion of the innovation as potential adopters may have gained general knowledge about the innovation for a long time. Therefore, we extract the first adoption week together with the median and the max adoption time from the database and deem that these could be informative on whether the late users become beneficiaries of the prior innovation growth.

Industry	Description	First Adoption Week (total week = 429)	Value distribution		Current % of total merchant uptake [5]
			Median	Max	
Retail	Includes traditional retails and liquor stores.	Week 36	3309	7730	18%
Restaurant and Cafe	Includes restaurants and cafes.	Week 1	2837	7096	16%
Supermarket	Includes supermarkets of varied sizes (i.e., chain stores, and independent superettes). The size effect is inherently captured by the terminal counting as larger supermarkets install more terminals.	Week 45	3795	5764	11%
Food	Includes butchery, bakery, takeaway food retailing.	Week 1	2607	5231	14%
Automobile	Includes petroleum/service stations and automotive repair and service.	Week 38	1489	4257	8%
Pharmacy and Beauty	Includes pharmacy, health services, hairdressing, and gyms.	Week 43	1481	4148	10%
Transport and Travel	Includes travel agencies, taxies, parking, and rental car services.	Week 63	1785	3991	6%
Entertainment / Hospitality	Includes entertainment, accommodation, book, music, and art related.	Week 1	3952	3150	7%
Clothing	Includes apparels and jewellery.	Week 32	815	2588	6%
Miscellaneous	Includes storage, postal services, telecommunication services, charities, education, and real estate.	Week 2	480	1939	3%
Government and Finance	Includes government, financial institutions, and insurance companies.	Week 72	58	275	1%

Table 16 Descriptive Merchant Adoption by Industry

[5] % obtained after industry consolidation in March 2020

3.4.3 Model-Free Evidence

A normalized plot between card diffusion and terminal diffusion is presented in Figure 7. Normalization is done via dividing the actual value for each series by its mean. The plot illustrates that terminal diffusion takes off slightly prior to card diffusion, but the two diffusion paths cling closely to each other especially in the early weeks. Diversion emerges after week 200, where terminal diffusion gathers significant momentum. The relative position changes again after week 320 when terminal diffusion appears to approach a bottleneck while card diffusion keeps soaring.

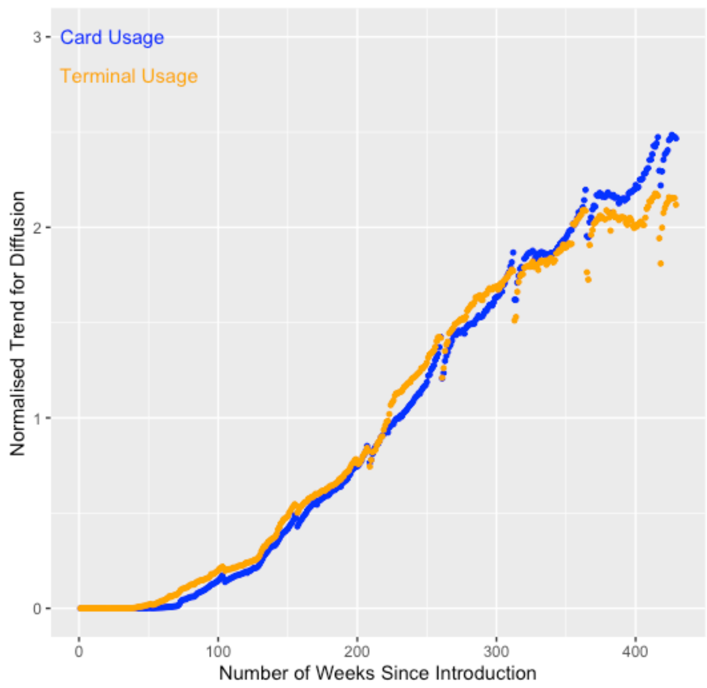


Figure 7 Normalized Card (Consumer) Diffusion vs. Terminal (Merchant) Diffusion

3.4.4 Modelling Approach

The classic Bass Model is parsimonious yet robust in modelling the diffusion of innovation (Wright et al., 1997). The model characterizes two different forces that drive the diffusion of innovation since its initial introduction (Bass, 1969). One force is termed the innovation effect, which depicts influences external to the social system that encourages innovators to pioneer in adopting the innovation and communicate their adoption decision and experience to the non-adopters. Research demonstrates that the fundamental role of innovation effect at the introduction stage of the innovation is vital for an innovation to diffuse. Without sufficient innovation effect, the target innovation has a limited chance of reaching the wider population. In contrast, adopters who choose to adopt as the result of influence from someone else’s adoption decision are called imitators. Imitators include both early adopters and late adopters, both of whom are subject to the influence of existing adopters. Bass (1969) argues that adoption decisions can be influenced by both innovative and imitative effects. However, the imitation effect kicks in after the innovation takes off and is deemed fuelling the rapid growth of the innovation towards its market potential. The market potential is defined as the ceiling of the number of adopters in a population and is usually assumed to be constant (Mahajan et al., 1979).

Extant research proposes modifications to account for diverse diffusion scenarios based on the classic Bass model. Relevant to the current study, Bucklin & Sengupta (1993b) examine the diffusion of complementary innovation – UPC symbol and scanners – by incorporating a co-diffusion effect as part of the innovation effect in the diffusion equations. Mahajan & Peterson (1978) is among the early work that investigates a dynamic market potential. Compared with a static ceiling of the number of adopters assumed in the classic Bass model, the authors suggest that the market potential shall be expressed as a function of previous adopters such that the ceiling of the number of adopters can be continuously increased alongside the diffusion process of the innovation. Unlike the majority of diffusion work focusing on consumer durables, Libai et al. (2009) modify the Bass model to fit the service industry. Given the pay-by-usage nature of service consumption, data is available for both adoption and churn or disadoption. Therefore, the authors include a retention rate, which equals to "1-disadoption or churn rate", applied to the innovation effect and the not-yet-adopting population.

We adopt the modified basic Bass model with churn rates introduced in Libai et al. (2009) to examine the diffusion of complementary innovation. Unlike innovation in consumer durables, service-type innovation incurs churn as the adopters can stop using the service temporarily or permanently. This pause or stop behaviour can be captured by the usage data, which is not quite feasible for consumer durables since the durables can only be captured at sales but not at dumping. Contactless cards are used by consumers and terminals that accept contactless payment are taken up by merchants. The model assumes that the probability of adoption for those who have not yet adopted the innovation is a linear function of those who have adopted and continued to use it at the time of being influential.

Our model specification is consistent with the equation in Libai et al. (2009), assuming that the leaving adopters may re-join the service at a later stage and thus shall not be excluded from the total adopting population. For the given data interval (i.e., weekly, bi-weekly, four-weekly), we share the perspective of existing literature that only the adopters who have not churned spread the word-of-mouth of the innovation (Libai et al., 2009).

Therefore, let δ be the churn rate we model, and the (1-δ) represents the proportion of remaining active adopters. Full model specification and deduction is shown as follows.

$$\frac{dN_i(t)}{dt} = p_i[m_i - N_i(t)] + q_i(1-\delta_i)\frac{N_i(t)}{m_i}[m_i - N_i(t)] - \delta_i N_i(t) \quad \text{(Eq1)}$$

Where:

$N_i(t)$ represents the number of contactless payment innovation adopters at the time t, and $i = 1$ represents the card usage, $i = 2$ represents terminal usage.

p_i is the real innovation effect for $i = 1, 2$;

q_i is the real imitation effect for $i = 1, 2$;

m_i is the real effective market potential for $i = 1, 2$.

By integrating equation (Eq1), the model gives the relationship between effect diffusion parameters and real diffusion parameters after accounting for the churn rate (δ).

$$\overline{m}_i = m_i \frac{\Delta_i + \beta_i}{2q_i(1-\delta_i)}$$

$$\overline{p}_i = \frac{\Delta_i - \beta_i}{2}$$

$$\overline{q}_i = \frac{\Delta_i + \beta_i}{2}$$

$\beta_i = q_i(1-\delta) - p - \delta_i$, and $\Delta_i = \sqrt{\beta_i^2 + 4q_i(1-\delta_i)p_i}$

where $i = 1$ represents the card usage, $i = 2$ represents terminal usage.

3.5 Results

We fit the data of card diffusion and terminal diffusion into Eq(1) respectively and estimate the model with nonlinear least square (NLS), an approach consistent with the NLS estimation adopted in Libai et al. (2009). In general, the model output shows satisfactory statistical power, with all parameters showing expected signs and levels of significance. The churn rates for merchant and consumer adoption are based on transaction data. Inclusion of churn rates results in a reasonable level of estimated market potential that approximates the current payment market size of the studied country – the total number of payment cards in use is around 5,280,000, and the number of active terminals on record sits around 150,000 in 2020 (data obtained by querying the database of the anonymous data provider). We provide model summary as follows – Table 17 presents the diffusion characteristics without the churn rate, and Table 18 presents the real diffusion parameters and market potential after accounting for the churn.

	Market potential (m)	Innovation effect (p)	Imitation effect (q)
Card Usage	2,240,204	0.00032	0.0146
	(p<0.001)	(p<0.001)	(p<0.001)
Terminal Usage	42,487	0.00034	0.0168
	(p<0.001)	(p<0.001)	(p<0.001)

Table 17 Model Summary – Bass Model without Churn Rate – Effective Estimates

	Market potential (m)	Innovation effect (p)	Imitation effect (q)	Churn rate
Card Usage	6,035,266	0.0001249	0.04045	0.025
Terminal Usage	155,727	0.0000941	0.06440	0.045

Table 18 Model Summary – Bass Model with Churn Rate – Real Estimates

It is evident that without the churn rates, card and terminal diffusion characteristics appear similar, while the indicated market potential for cards and terminals deviates far from the actual volume. After accounting for the churn rates, the diffusion characteristics, namely the innovation effects and imitation effects, diverge, with the market potential for cards and terminals becoming realistic.

By reviewing the overall model fit and the predicting power, we conclude that the proposed Bass Model with churn rates works better for merchant usage than consumer usage. All key parameters, namely the innovation effect, imitation effect, and market potential, show reasonable signs and magnitudes, with strong statistical significance. By splitting the data into 75% training and 25% validation subsets, the Mean Absolute Percentage Error (MAPE) and Root-Mean-Square Deviation (RMSE) measurements are calculated for both the fitted values (fitted by the training data) and predicted values (predicted with the validation data). Merchant usage consistently shows lower values in both measurements than consumer usage, indicating a better model fit. It is noted that the given the real data in the validation subset has higher values, the Correlation Coefficient and RMSE are greater in magnitude, as those metrics are in absolute terms. It is seen from the MAPE, which is not impacted by the magnitude of the actual values, that the measurement on validation data does not deteriorate. Refer to the following table for details.

	Training			Validation		
	Correlation Coefficient (r)	MAPE[6]	RMSE	Correlation Coefficient (r)	MAPE	RMSE
Card adoption	0.9982 ($p<0.001$)	0.1149	33,129.94	0.9343 ($p<0.001$)	0.0610	155,173.4
Terminal Adoption	0.9975 ($p<0.001$)	0.0500	894.0201	0.8347 ($p<0.001$)	0.0275	1,397.3430

Table 19 Model Diagnostic Summary

<u>RQ1 Key Results – The Bass model fits the data well; Imitation effect drives merchant adoption while innovation effect fuels consumer adoption.</u>

By comparing the size of effects of both innovators and imitators on the diffusion paths, we observe that the diffusion of co-dependent innovation relies much on the imitation effect in each adopting group. When comparing the magnitudes of the diffusion drivers found in the current study against the average size of effects summarised in diffusion literature, we notice a sizable difference, as our p_i and q_i are much smaller than average values. Chandrasekaran & Tellis (2015) records the mean values of the coefficient of innovation are ranged between 0.0007 and 0.03, while the range of coefficient of imitation is between 0.38 to 0.53. Our results for both adopting groups fall outside of these thresholds. One explanation could be that innovators may be scant at the introduction stage of the innovation due to the higher uncertainties inherent in the co-dependent pair. Unlike independent innovation that can be adopted and used alone, co-dependent innovation requires to be adopted and used jointly. Therefore, anyone who is genuinely willing to adopt the contactless payment innovation may ask the question of whether there will be sufficient adoption taken by the other user group to enable the actual usage. Another possible explanation is that the parameter estimates are lower due to the higher data granularity in the current research compared to other Bass modelling studies. These explanations are not mutually exclusive.

<u>RQ2 Key Results – Churn rates help depict the diffusion pattern better.</u>

Results suggest that incorporating churn rates in the context of the diffusion of contactless payment innovation is critical, as the estimated size of market potential only appears to be reasonable when the churn rates are accounted for (Table 18). Data shows that by the end of December 2020, the number of active payment cards used in contactless transactions reached 4,000,000, and the number of merchant terminals accepting contactless

[6] Note: For training model performance, MAPE is calculated on left trimmed data to exclude the early fluctuations commonly observed in diffusion time series.

payments reached 64,000. Under the Bass modelling framework, the market potential without churn rates predicts merely 2,000,000 for card usage and 420,000 for terminals, leaving no room to grow. Ceteris paribus, the market potential predicts to be 4,000,000 and 155,000 respectively, when the churn rate is accounted for. Therefore, the model without churn rates significantly underestimates the market potential for both diffusion paths. With the vastly different market potential, it is reasonable to assume that the associated innovation effect and imitation effect estimated by the Bass model without churn are by no means accurate.

As shown in Libai et al. (2009), churn rates impact the diffusion parameters differently. Given the limitation of our data, we do not obtain the actual weekly churn rates by tracking the contactless payment usage of every card and terminal, as this requires comparing 5 million transactions daily. Instead, we model the churn rates based on the realistic market potential. Results show that the churn rate for consumers sits around 2.5%, while the churn rate for merchants reaches 4.5% on a weekly basis. It is not surprising to see merchants showing a higher churn rate than consumers, given the fact that merchants shoulder the costs of enabling contactless payment by paying transaction surcharges. The potential benefits of accepting contactless payment for merchants include increased efficiency at the checkout during peak hours and consumers' appreciation of the convenience of paying. If those benefits can be translated into more business or more returning consumers, the merchants will be willing to pay for the costs. Otherwise, the increased costs may only drag down the profits and lead to discontinued acceptance of the pricy payment innovations.

After accounting for the churn, the real innovation effect of consumer usage reduces by 60% and its real imitation effect sees a large increase of 170%. The movement for merchant usage is even greater, with a 72% drop in the real innovation effect and a 283% gain in the imitation effect. The existence of churn rates steers the driving force of diffusion towards the imitation effects, but the magnitude of the steering differs between merchants and consumers. Thus, increases in churn rates impact the innovation effects and imitation effect in different directions, indicating that the parameters of Bass model without churn rate can be severely affected by omitted variable bias in the context of co-dependent diffusion of service innovations.

3.6 Robustness Tests

To test the robustness of the results, we re-run the model with bi-weekly and four-weekly data of both consumers and merchants. Bass (1969) indicates that the diffusion parameters can depend on the time scale used in the modelling. Therefore, we expect the magnitudes of p and q to vary when plugging in bi-weekly and four-weekly data. However, the relative strength of the innovation and imitation effects for consumer usage and merchant usage is expected to be consistent with the weekly output. That means, after accounting for the churn rates, merchant usage tends to have a lower innovation effect and higher imitation effect than consumer usage. We also expect the model fit of merchant usage remains to be better than that of consumer.

Results confirm that the pattern identified with weekly data of merchant and consumer usage is robust (Refer to Table 17 & Table 18 for Model Summary of the original model and the Appendix B for Robustness Test Results). In addition, the modelling outputs with four-weekly data shed light on the changes of churn rates. When data interval increases from bi-weekly to four-weekly, the churn rates significantly increase for both consumer usage and merchant usage. This meets the expectation that over a longer period, users' intention to continuously use the innovation is subject to change. The hikes in modelled churn rates for both user groups, merchant group and consumer group alike, suggest that more users tend to stop using contactless payment methods when they experience the innovation for more than two weeks. Evidence shows that merchants are more likely to dis-adopt than consumers, given a 77% increase in merchant churn while a 40% increase in consumer churn. Without further investigating the reasons behind the churn rates for both groups, we offer one potential explanation, which could be the interaction outcome between the merchants and consumers discourages a proportion of users and thus drives them away. Since merchants are burdened with the contactless payment surcharges and consumers gain a free ride, merchants tend to churn if the expenses are not justified, and consumers tend to stop using contactless payment if the merchants patronised refuse to accept this means of paying anymore. In sum, our findings are robust by delivering a consistent pattern of diffusion for merchants and consumers with different granularity levels of data and unveil the changes in churn rates for both adopting groups with different time spans.

3.7 Simulation on Churn Rates

As the churn rate impacts the parameters of the modelling output, we further investigate how changes in the churn rates will be translated into changes in the diffusion parameters. Taking merchant usage as an exemplar case, with the effective diffusion parameters determined by the data, we rely on the computer-simulating procedure to generate stochastic churn rates to provide statistical estimates of the real innovation effect, imitation effect, and market potential (Alvarez & Lippi, 2013). This approach will shed light on the impact of different churn rates on the three key parameters used to describe the diffusion of co-dependent innovation on the merchant side.

The modelling output shows an average churn rate of merchant usage at 0.045. Therefore, the simulation process specifies 10,000 random draws from a uniform distribution bounded by 0 and 0.1, indicating that each random number between 0 and 0.1 has an equal likelihood of being drawn. We share the simulating information as below:

	Distribution	Interval	Number of iterations	Mean
Churn rate	Uniform	(0,0.1)	10,000	0.04975

Table 20 Summary of Simulated Churn Rates

By incorporating the randomized churn rates into the real diffusion modelling, we generate 10,000 corresponding sets of real diffusion parameters. The average simulated market potential (m) is 167,807, 7.76% higher than results from the real diffusion based on data but is close to the total number of terminals registered in the database of the payment provider. Therefore, the simulation is feasible given that the simulated market potential illustrates an ideal world that all merchants accept the contactless payment in the end. The average simulated innovation effect (p) is 0.0001127, slightly lower than the innovation effect at 0.0001249 based on data. The increase of the market potential and the drop in the innovation effect imply declining importance of innovators in the diffusion of contactless payment innovation. Larger driving force may come into play after some users in the group adopt and continue to use the innovation. This idea is echoed with the result of the mean simulated imitation effect, which proves to be 9.86% larger than the imitation effect based on data.

Variable	Min	1st Quantile	Median	Mean	3rd Quantile	Max
Innovation effect (p)	0.00004958	0.00006358	0.00008752	0.0001127	0.0001379	0.0003439
Imitation effect (q)	0.0168	0.04296	0.06942	0.07076	0.09815	0.12943
Market potential (m)	42,504	105,960	166,989	167,807	229,894	294,777

Table 21 Simulated Model Output

The simulation results help describe how the market potential and the two driving forces of diffusion will change as a result of changed churn rates within a specified range. Since the churn rates for co-dependent innovation also embody whether both adopting groups are willing to continue use the innovation based on their interactions, the relationships between churn rates and the simulated innovation and imitation effects are also informative. Figure 8 & 9 present the density plots for churn rates associated with the two diffusion characteristics respectively. It is observed that the churn rates are positively associated with imitation effects, as higher churn rates may imply higher imitation effects. On the contrary, churn rates negatively relate to the innovation effect, and the highest innovation effect occurs when the churn rate equals zero. The pattern density also unveils that the simulated innovation effect tends to concentrate on a lower range, i.e., between 0.00005 and 0.00015, with churn rates spanning from 0.02 to 0.08.

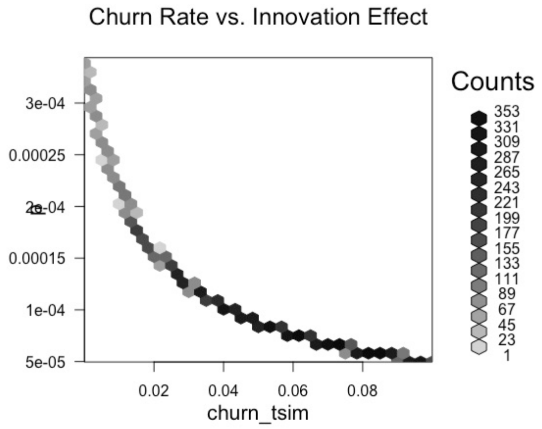


Figure 8 Simulated Churn Rate vs. Innovation Effect.

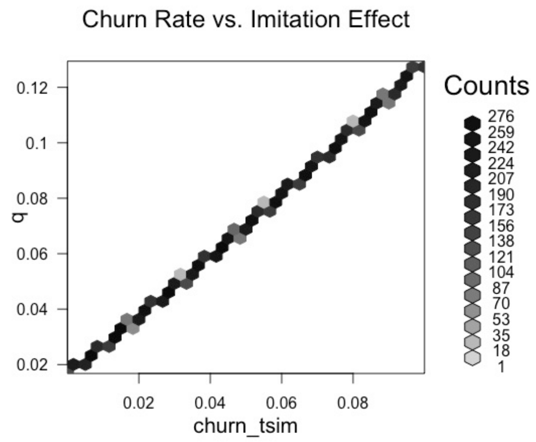


Figure 9 Simulated Churn Rate vs Imitation Effect

3.8 Exploring Merchant Usage by Industry

Prior literature either selects a subset of related industries for analysis (Stremersch et al., 2007) or examines the size of the merchants on top of their behaviour (Bucklin & Sengupta, 1993b). None of the prior work examines the diffusion of innovation across all major industries. Given the rich data set, our current work is able to assess the diffusion of complementary innovation across all industries (later grouped into 11 major categories) in the studied country. This provides some interesting managerial implications as well as a further robustness check on the main results.

Relying on the Standard Industry Code (SIC) information associated with each merchant that operates terminals, we group all terminals used in the contactless transaction by industry. After evaluating the nature of the business, we combine some similar industries into a more conclusive one to reduce the undesired nuances in the findings. For instance, "Entertainment and Hospitality" takes in "Book and Video" as well as "Music and Photography" as the latter two are both activities for leisure time. The number of terminals is also a consideration, leading to a moving-out of the food category from a general "Supermarket and Food" group. After the consolidation, ten main categories and one miscellaneous category are ready for modelling.

Data shows that 18% of the contactless payment enabled terminals are used by retail merchants, followed by 16% by those running restaurants and cafés at the end of 2020. It is not surprising that merchants in retailing and dining segments welcome contactless payment the most. However, the model output of merchant usage by industry reports two interesting findings, discussed in the following paragraphs. A detailed model summary of merchant usage per industry can be found in Appendix C.

<u>RQ3 Key Results – Late-adopting industries tend to show higher churn rates, while early-adopting industries build solid user bases and witness less churning.</u>

The Transportation and Travel industry exhibits the highest imitation effect ($q = 0.1432$), which is almost ten times larger than the imitation effect of the merchant population overall. By reviewing the first adoption week for this category, we notice that merchants in this industry took up contactless payments relatively late (week = 63, which is more than one year later than the earliest adopters). Late entrants to the market, although missing the benefits of first movers, tend to have an easier adopting environment, with more mature techniques of innovation and higher willingness to use among consumers, as the result of the growing size of early adopters. However, the Transportation and Travel industry also scores the highest churn rate among the 11 industries, indicating that an unstable early adopter group within the industry tends to fail the mission of consistently driving the usage of contactless payment innovation.

Merchants in the Automobile industry are motivated to be early adopters of contactless payment ($p = 0.000465$, which is four times higher than the merchants across all industries). As merchants categorised in the automobile industry include service stations, the willingness to become early adopters is justified by the importance of having a quick checkout process for service station merchants. Drivers are keen to get back on the road, and merchants are keen to increase the turnover by reducing the queuing time, since there is a limited number of pumps per station. A slow check-out process will end up with long queues and low turnover, potentially turning drivers away as long as they have sufficient fuel to patronise another service station nearby. Therefore, in the case of automobile merchant adoption of contactless payment method, results confirm the importance of matching the characteristics of innovation with the top business need to fuel the diffusion rate.

The Bass model with churn rate generally fits well with all industries, with a high correlation of coefficient (i.e., average r = 0.988) between actual values and predicted values per industry and a low RMSE (i.e., average RMSE = 197.313) across all industries studied. The magnitude of RMSE depends on the range of the raw data. Therefore, considering our data for merchant adoption ranges from 12 to 42,683, we deem the calculated RMSE, although large in magnitude, can still be plausible. Note that the calculation of r and RMSE is not weighted by the number of merchants in each industry. We present the plots of model fit for 11 industries in Appendix C, where actual values are in blue, and the fitted values are in orange. Here we comment on four typical examples, showing some of the best and worse model fit. We see an obvious deviation from the general S-shaped diffusion paths for merchants in “Automobile” and “Transportation and Travel” industries. However, the diffusion plots of contactless payment among merchants in the “Restaurant and Café” and “Entertainment/Hospitality” industries demonstrate great model fit, as the actual data closely aligns with the fitted plots.

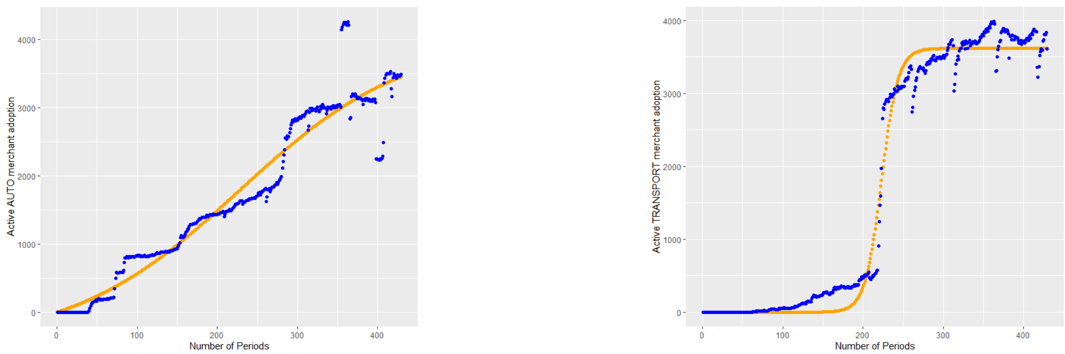


Figure 10 Merchant Usage in Automobile Industry & Transportation Industry

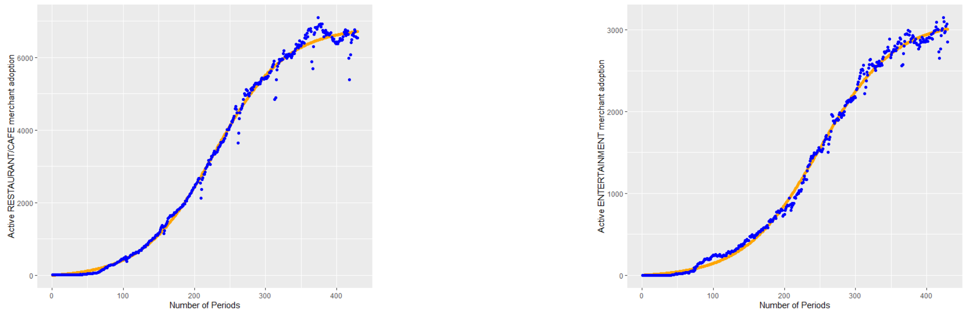


Figure 11 Merchant Usage in Restaurant and Café & Entertainment/Hospitality Industry

3.9 Summary and Discussion of Key Findings

The current study employs the Bass modelling approach to study the diffusion of co-dependent service innovations. Results confirm that the diffusion paths of the co-dependent innovations differ among the adopting groups (RQ1). Specifically, the imitation effect drives diffusion on the merchant side, indicating intense peer pressure among merchants towards adoption and usage. In contrast, diffusion on the consumer side is fuelled by the innovation effect as the result of external influence (RQ1). By comparing the modelling output with and without churn configuration, we confirm the importance of accounting for the churn rates in the co-dependent diffusion. Therefore, churn rates can be used as a proxy of the interaction and thus to depict the feedback between the co-dependent groups (RQ2). Applying the Bass modelling to 11 main industries in the studied country, we provide substantive evidence of how co-dependent innovation diffuses across industries and highlight the results against the common wisdom about innovation uptake (RQ3). The key takeaway of the current study can be summarised in the following three aspects.

We answer RQ1 by confirming that the diffusion of co-dependent innovation differs between the merchant and consumer adopting group with the Bass model. The parsimonious yet robust Bass model shows that the diffusion among merchants has higher imitation effects than that among consumers, with and without churn rate accounted for. Consumers show a lower imitation effect and a similar innovation effect as with merchants when consumer churn is not accounted for. However, accounting for the churn rate reverses the relative sizes of innovation effects of consumers and merchants, with greater innovation effect found in the card diffusion. This reversal reveals a stronger persuasion from external communication, i.e., mass media advertising (Lee et al., 2014) for consumers' usage decision. Moreover, the inclusion of churn rate pushes the imitation effect on the merchant side to be the dominant forces in driving the diffusion, as the innovation effect slides while the imitation effect gets a boost. Merchants, therefore, show greater responsiveness to word-of-mouth or peer pressure in their usage decision of co-dependent innovation. The model fit for the diffusion by consumer and merchant groups proves plausible, with high correlation coefficients and low deviations between the predicted and actual data points.

We propose the churn rate as the proxy for the interaction between the adopting groups in the diffusion of co-dependent innovation. Consumers will churn if they continuously get unsatisfactory experiences when their usage decisions mismatch with merchants'. A similar situation applies to merchants. Hence, the churn rate's relative size represents the interaction outcome. It is evidenced that when accounting for the churn rates, the model output satisfies the face validity and demonstrates good statistical and predictive validity. By simulating the churn rates for the merchant group, we depict how changes in the merchant churn impacts the diffusion characteristics of contactless payment terminals.

Our examination of the 11 industries (treating Restaurant and Café separately from the Entertainment and Hospitality industry) covers the whole population of the active merchants in the studied country and answers our third research question regarding the industry-specific impact. We are the first to study the usage behaviour of merchants by industry, and the results are informative in the following three aspects. The diffusion of contactless payment in the restaurants and cafes is in line with our expectation, such that the diffusion rate is strong, (i.e., the combined real innovation and imitation effect combined reaches 0.0513), driven by merchants' desire to facilitate the check-out process and bring consumers more easiness and convenience. However, our common knowledge about merchants in dining services does not secure them with any leading position of innovation effect nor imitation effect in the diffusion of contactless payment, since neither the effects top those of remaining merchants in other industries.

As discussed in the result section, we see that the "Automobile" industry leads the real innovation effect in contactless payment uptake. When linking the constituent members in the automobile industry to this unexpected result, we find this strong innovation effect makes good sense. Services stations constitute a large portion of merchants in the automobile industry, and speedy checkout is in high demand at service stations, given the limited number of petrol pumps. Contactless payment innovation outperforms all the other means of payment by providing a smooth and fast check-out process. Therefore, matching the contactless payment features with the merchants' needs contributes to the early adoption of contactless payment, implying a strong innovation effect, in the automobile industry.

Another diffusion surprise comes from the "Transport and Travel" industry, where a sharp uptake of contactless payment happened between week 200 and 215. As the result, modelling outputs for merchants in transport and travel show a high imitation effect, three times larger than the "Restaurant and Café" industry. Three facts draw our attention to dive into the details of the merchants in this industry. First, merchants classified in this category are taxis, rental car companies and public parking operators. As those businesses are likely to be run in a large scale, we have reason to believe that the usage decisions may come from a high level and are applied to many terminals in a short time. Second, we notice the first adoption week for this industry is rather late (i.e., week 63), which confirms our postulation that if the decision comes from the management, the management would surely like to see the usage picks up successfully in other industries first. Lastly, a high churn rate found in the "Transport and Travel" industry may indicate there are some drawbacks or at least frictions when trying to take advantage of some already popular innovation without a solid user base. This flip of churn may discourage users from the other group, i.e., consumers, when they use contactless payment successfully for one taxi ride but then find the payment is not accepted in their next ride.

To our best knowledge, the current study is the first of the kind to simulate churn rates for modelling and to provide density plots for the relationship between churn rates and the innovation and imitation effects. Other research opts a specific churn rate from the data or uses an industry average as the proxy. The plots (i.e., Figure 8) show a non-linear relationship between churn rates and innovation effect, indicating a greater deduction in innovation effect when churning just starts to emerge.

3.10 Limitations and Future Research Opportunities

Although our study presents some interesting findings of the diffusion of complementary payment innovation among merchants, we acknowledge that there are limitations in aspects of data measurement, model specification and the context of a single market.

<u>Data Measurement</u>

Diffusion of consumer durables is typically examined with sales data. Although there is criticism regarding the starting date of the sales to be accounted for, and the fact that the sales usually fail to distinguish first adopters from returning customers, measuring diffusion by sales is still a widely acceptable practice. However, in the diffusion of service domain, there is not much dedicated guidance on the measurement of service usage outcome.

Diffusion of service can be examined through sampled households with a decision-based measurement on whether to use it or not (Datta et al., 2015). However, the sampling approach is less realistic in the diffusion studies, as the diffusion is supposed to be studied against the whole population, which consists of innovators, early adopters, and laggards who are those late adopters. It is not feasible to know beforehand who are the innovators and who are the laggards to construct a stratified sample that approximates the population. Therefore, the diffusion of service still relies on the outcome variable, such as the number of subscriptions and/or registrations to approximate sales in the consumer durable categories (Hogan et al., 2003; Lilien et al., 2000). In the current study, we aim to use the analogy of subscription in the payment market and adopt the transaction-based measurement for the usage of contactless payment by both merchants and consumers. We opt for transaction-based over the configuration-based for the reason discussed in prior section. In addition, we find transaction-based measurement aligns with the number of subscribers in that both measurements associate with the paying-by-usage notion. Configuration alone will not incur any cost of use, so it fails to accurately depict adoption and usage.

However, we acknowledge that the chosen data measurement still shares the shortcoming of not being able to distinguish first users from returning users as with most data used in the diffusion of consumer durables innovation. Flagging the first usage of terminals and cards is deemed redundant in the payment system, as the key focus of the payment provider is to ensure continued usage of both adopting groups. As our data provider does not pursue this flagging practice at the introduction of the contactless payment, retrospectively adding a flag to the terminal ID and card ID is computationally demanding. Not to mention that if first adopters disadopt after their first trial, they are not much different from the other non-adopters in the aspect that no positive word of mouth will be spread. This is starkly different from the adoption of consumer durables, where a purchase distinguishes adopters from non-adopters due to the financial commitment. Therefore, our data set does not differ between first and returning users. We believe the count of total distinct cards and terminals at each snapshot time shall ease the concern of whether the user is a first adopter or not.

Model Specification

The current study adopts the Bass model with churn rates to model the diffusion of co-dependent innovation. Although the output exhibits a satisfactory model fit, and the churn rates appear to be a good proxy of the feedback between the adopting groups, we see two limitations associated with this modelling approach. First and foremost, the model does not explicitly incorporate lag terms to show which adopting group moves first and how one group reacts to the diffusion outcome of the other group. As the key objective of the current study is to demonstrate the difference between adopting groups in terms of co-dependent diffusion, we assume no lagging effect at this stage. A related issue is that the Bass model parameters are fixed throughout the diffusion process, and this may fail to fully account for the dynamic effects present in the diffusion of co-dependent innovations. Alternative models, such as Vector Autoregression Model (VAR) and Vector Error Correction Model (VECM), may account for the simultaneous estimation and asymmetric temporal effect along the diffusion process.

In addition, we acknowledge that the use of churn rates as a proxy for the feedback represents a hindsight measurement that is not available for predicting diffusion outcomes. Given the payment market context, it is unfeasible to track the usage of individual cards and terminals in contactless transactions among 5 million transactions per day. Further research should consider other measurements as the proxy of interaction or utilise a recursive algorithm with greater computing power to track the actual interaction rates between co-dependent innovations in contexts other than the payment market.

Single Market Context

We only study the diffusion of contactless payment in a single market. According to the “Global Innovation Index 2021” report (WIPO, 2021), the overall innovation input and output of the studied country is ranked in the top 20 in 2020. The country is viewed as “performance in line with level of development”, sharing the same comment as a few European countries. In the index, there are countries rated as outperformed – innovation performance above their levels of economic development, such as Sweden, Switzerland, the US, and the UK. It would be informative to choose countries stratify-sampled by innovation ratings to examine the patterns of the diffusion of co-dependent innovation across countries.

In addition, the studied country is considered a late adopter of the contactless payment innovation, with around 27% of in-store transactions being contactless at the beginning of 2020. For some European countries, such as Denmark, Poland and Netherlands, this number has been over 50% since 2018 (De Best, 2019). As the contactless payment markets in those countries may approach market saturation and thus possess data that cover both the take-off and the slowdown stages, it will be interesting to apply the modelling approach of the current study to those mature markets and gauge the impact of churn rates on diffusion stages.

Appendix B Robustness Test Results

Table 1.1 Summary Table with Bi-weekly data

Variable	Min	1st Quantile	Median	Mean	3rd Quantile	Max	Correlation with Card Adoption
Card Usage	86	227,403	1,029,441	1,147,716	2,066,436	2,766,449	1
Terminal Usage	15	4,390	18,336	20,917	37,029	45,115	0.9959

Table 1.2 Summary Table with Four-weekly data

Variable	Min	1st Quantile	Median	Mean	3rd Quantile	Max	Correlation with Card Adoption
Card Usage	170	336,740	1,302,724	1,418,171	2,511,988	3,383,582	1
Terminal Usage	19	4,636	19,367	22,213	39,214	47,755	0.9963

Table 2.1 Modelling Output of Effective Diffusion with Bi-weekly Data

	Market potential (m)	Innovation effect (p)	Imitation effect (q)
Card Usage	2,240,204	0.00080	0.0274
	($p<0.001$)	($p<0.001$)	($p<0.001$)
Terminal Usage	45,125	0.0007	0.0335
	($p<0.001$)	($p<0.001$)	($p<0.001$)

Table 2.2 Modelling Output of Effective Diffusion with Four-weekly Data

	Market potential (m)	Innovation effect (p)	Imitation effect (q)
Card Usage	3,350,656	0.0018	0.0541
	($p<0.001$)	($p<0.001$)	($p<0.001$)
Terminal Usage	47,920	0.0014	0.0672
	($p<0.001$)	($p<0.001$)	($p<0.001$)

Table 3.1 Modelling Output of Real Diffusion with Bi-weekly Data

	Market potential (m)	Innovation effect (p)	Imitation effect (q)	Churn rate
Card Usage	5,355,345	0.000421	0.05337	0.025
	($p<0.001$)	($p<0.001$)	($p<0.001$)	
Terminal Usage	105,162	0.000294	0.08181	0.045
	($p<0.001$)	($p<0.001$)	($p<0.001$)	

Table 3.2 Modelling Output of Real Diffusion with Four-weekly Data

	Market potential (m)	Innovation effect (p)	Imitation effect (q)	Churn rate
Card Usage	5,472,885 ($p<0.001$)	0.001128 ($p<0.001$)	0.09163 ($p<0.001$)	0.035
Terminal Usage	104,382 ($p<0.001$)	0.000629 ($p<0.001$)	0.15927 ($p<0.001$)	0.08

Table 4.1 Model Diagnostic Table with Bi-Weekly Data

	Training			Validation		
	Correlation Coefficient (r)	MAPE	RMSE	Correlation Coefficient (r)	MAPE	RMSE
Card Usage	0.9980 ($p<0.001$)	0.1056	37,852.24	0.9400 ($p<0.001$)	0.0921	264,657.9
Terminal Usage	0.9979 ($p<0.001$)	0.04872	799.9036	0.9057 ($p<0.001$)	0.0375	1881.034

Table 4.2 Model Diagnostic Table with Four-Weekly Data

	Training			Validation		
	Correlation Coefficient (r)	MAPE	RMSE	Correlation Coefficient (r)	MAPE	RMSE
Card Usage	0.9976 ($p<0.001$)	0.1154	48,819.39	0.8845 ($p<0.001$)	0.0881	309,814.2
Terminal Usage	0.9981 ($p<0.001$)	0.0487	802.3474	0.9157 ($p<0.001$)	0.0326	1656.586

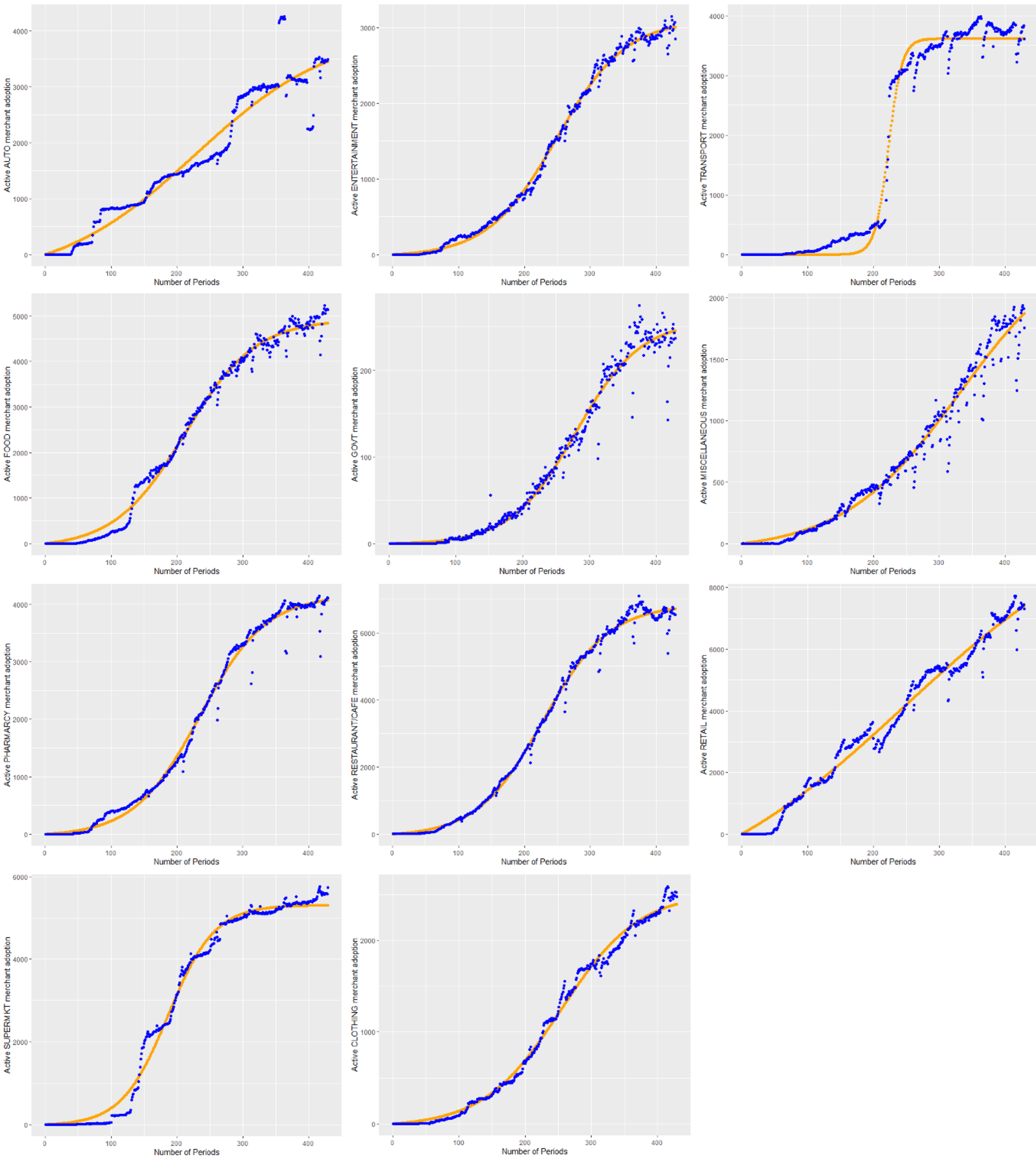
Appendix C Merchant Usage by Industry

Table 1 Model Summary and Model Fitness

Industry	Real market potential (m)	Real innovation effect (p)	Real imitation effect (q)	Churn rate[7]	Predictive power	
					Correlation	RMSE
Retail	27,247	0.00043741	0.01222	0.008	0.9904	325.8166
Restaurant and Cafe	17,132	0.00008468	0.05124	0.03	0.9978	169.4665
Supermarket	9,075	0.00008340	0.03853	0.02	0.9955	216.7826
Food	10,261	0.00016816	0.03892	0.02	0.9960	170.5483
Automobile	8,463	0.00046501	0.01826	0.01	0.9649	301.5220
Pharmacy and Beauty	8,345	0.00009285	0.04052	0.02	0.9591	517.9531
Transport and Travel	5,105	0.00000119	0.14319	0.04	0.9921	220.9752
Entertainment/ Hospitality	6,380	0.00008333	0.03853	0.02	0.9981	69.6504
Clothing	5,507	0.00010176	0.03739	0.02	0.9970	68.1058
Miscellaneous	4,806	0.00013760	0.02103	0.01	0.9869	97.1331
Government and Finance	637	0.00002491	0.05190	0.03	0.9903	12.5391

[7] Churn rate is obtained on the weekly basis to match the data used in the model.

Figure 2 Plots of Diffusion among Merchants by Industries



Appendix D Statement of Contribution

DRC 16

MASSEY UNIVERSITY
TE KUNENGA KI PŪREHUROA
UNIVERSITY OF NEW ZEALAND

GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Xing (Alison) Chen
Name/title of Primary Supervisor:	Prof. Malcolm J. Wright
In which chapter is the manuscript /published work:	Chapter 3

Please select one of the following three options:

( ) The manuscript/published work is published or in press

- Please provide the full reference of the Research Output:

( ) The manuscript is currently under review for publication – please indicate:

- The name of the journal:
- The percentage of the manuscript/published work that was contributed by the candidate: 60.00
- Describe the contribution that the candidate has made to the manuscript/published work:

The candidate completed the research design, literature review, model specification, analysis and writing. The role of the supervisors has been restricted to assisting with the conceptualisation of the project, advisory comments on research design and analysis, and critical evaluation and editorial comments on written drafts.

(•) It is intended that the manuscript will be published, but it has not yet been submitted to a journal

Candidate's Signature:	Xing Chen Digitally signed by Xing Chen Date: 2022.09.17 23:32:56 +12'00'
Date:	17-Sep-2022
Primary Supervisor's Signature:	Wright, Malcolm Digitally signed by Wright, Malcolm Date: 2022.09.18 11:39:08 +12'00'
Date:	18-Sep-2022

This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis.

GRS Version 5 – 13 December 2019
DRC 19/09/10

Chapter 4 Dynamic Effects in Co-dependent Diffusion of Innovation

Abstract

Technological change has increasingly led to innovations requiring uptake by more than one population. To diffuse, those innovations rely on two-sided markets, such as digital marketplaces that connect groups of buyers and sellers (e.g., Alibaba, AirBnB, Uber) as well as networks formed by two populations, each adopting component innovations (e.g., electric cars and charging stations, or contactless payment terminals and contactless payment instruments). A key feature of two-sided markets is that the attractiveness of the innovation to one population (e.g., drivers) depends on the level of adoption by the other population (e.g., riders). Hence there is co-dependency. The current study examines dynamic effects in the diffusion of contactless payment innovation in a developed western country. Applying the Vector Error Correction Model (VECM) to eight years of weekly payment data reveals the pattern of the interactions and short and long-term effects in the innovation diffusion between the consumer and merchant adopting groups. There is a co-dependent relationship between the two, with consumers showing more significant response to the variation in merchant usage than vice versa. This insight goes against the common wisdom that merchants, as the cost-bearers of the innovation, will be more responsive to a consumer usage shock. These effects are time-varying, with the interaction prominent in the early years since the introduction of the innovation, decaying to insignificant before the diffusion plateaued. Results indicate that platform operators can tailor their user acquisition strategies to accommodate the needs of the more sensitive adopting group by sustaining the usage at the early stage to drive diffusion in the long run.

Keyword:

Co-dependent diffusion, network effects, two-sided market, Vector Error Correction Model

4.1 Introduction

Platform-based markets such as eBay.com, AirBnB and Uber are typical two-sided markets where the marketplaces act as the intermediary that connects suppliers to customers and vice versa, aiming to get both sides to subscribe to the platform (Eisenmann et al., 2006; Muzellec et al., 2015; Rochet & Tirole, 2003). However, there are other two-sided markets where the participating groups interact directly without, or with minimal, intermediary facilitation. The success of those markets relies on direct interactions between each participating side rather than interactions with the market platform. While the characteristics of the two-sided markets determine interest in the initial adoption, continued usage after the adoption is based on the subsequent reactions of one side on knowing the usage decisions from the other side. For instance, card users will use cards for purchases if sufficient merchants continue accepting transactions by cards. Electric vehicle drivers will purchase and drive electric vehicles if they know that charging stations are easy to find along their trips. This type of two-sided market breeds a new diffusion pattern of innovation specific to those markets, where the innovations require continuous adoption efforts from both sides to sustain the diffusion process through positive feedback. The current study investigates this diffusion pattern, termed as the co-dependent diffusion of innovation in two-sided markets based on the dependency between the adopting groups.

At present, co-dependent diffusion of innovation is hardly studied, yet has become a more frequent phenomenon with ongoing technological development and disruption of existing markets. Prior literature on diffusion of innovation examines the characteristics of the innovation, the preferences of potential adopters, and strategies of platform operators to boost diffusion. However, the co-dependency between the adopting groups and the feedback loops between them remains unexplored. To fill the gap in the literature, the current study leverages a unique data set containing eight years of weekly usage data of a typical two-sided market, that is, the contactless payment market. Contactless payment methods, provide a smooth paying experience at the checkout without the hassle of requesting users to insert the card and key in the PIN for small-value purchases. Contactless payment is a typical two-sided market because it relies on the joint uptake and usage of the innovation by two distinguished populations – merchants and consumers (Rochet & Tirole, 2006).

The current study has two focuses. First, we examine the co-dependency between the demand of both sides of the market for the diffusion of innovation. Specifically, we adopt Vector Error Correction Model (VECM) approach to describe the diffusion characteristics, such as 1) the magnitude of the driving forces of the diffusion within each adopting population and 2) the symmetry of the feedback effect as a result of the interactions between the adopting populations. Second, we investigate the dynamics of the interaction for innovation diffused in the two-sided market. The dynamics are tested in two ways. One is through the Impulse Response Functions (IRF) based on the VECM with lagged effect and error correction terms. The other is through the moving window analysis, where the diffusion penetration grows in the market, providing a changing setting for the adopting groups to interact.

Results confirm the co-dependency between the adopting groups by showing the responsiveness in the usage level of one side when the usage of the other side changes. Consumers are found to be more responsive to changes in the merchants' usage than the other way around. Results also show a positive interaction effect between adopting groups in the short term but a divergent trend of this two-way enhancement in the long run. Merchants' usage change shows a permanent uplift in consumers' usage, consumers' usage change exhibits a much smaller positive impact on merchants. In addition, the interaction is stronger in the early stage of diffusion and decays as the market moves closer to saturation. The knowledge provides insight for market promoters about whom to target, what customer acquisition plan shall be effective and how to tilt strategy during different stages of the diffusion.

The study is organised as follows. In the next section, we review seminal papers in relevant research streams and point out the research gaps that the current work aims to fill. Then we describe the study framework and state the research questions with testable hypotheses. Data and methodology are introduced in the following section and results are discussed after that. We conclude the study with a general discussion and managerial implications, pointing to possible directions for future research.

4.2 Theoretical Background

Rogers (1983) proposed diffusion of innovation as a process by which an idea is communicated through a social system over time. Diffusion has since been extensively researched in the marketing domain as it applies to the consumer market (e.g., Mahajan and Muller 1979; Norton and Bass 1987). However, diffusion can be complicated by factors such as the release of successive generations of new technology prior to saturation (e.g., microchips), the requirement of purchasing complementary products by the same consumers (e.g., gaming consoles and games, or software platforms and apps), or the requirement of simultaneous uptake by multiple adopting groups, resulting a dependency between the groups that either fuels or constrains the diffusion of the innovation. Given the nature of the innovations diffused in two-sided markets, research has examined this last complication, with discussion of potentially relevant work on the diffusion of interrelated innovations, two-sided markets, and network effects.

4.2.1 Diffusion of Interrelated Innovation

In his seminal work, Rogers (1983) introduces the notion of technology clusters and points out the research direction of understanding complexes of innovation and how individuals perceive interrelated ideas. Promoting a cluster or package of innovation may lead to a more rapid uptake in the market. To pursue this research direction, Bayus (1987) forecasts the adoption of software contingent on the adoption of compatible hardware. Dewan et al. (2010) examined the co-diffusion phenomenon between PCs and the Internet, finding that the diffusion of PCs stimulates the diffusion of the Internet. Similarly, after reaching the take-off point, the innovation that requires investment in complementary infrastructure gathers a higher diffusion rate than the standalone innovation (Van Den Bulte 2000). It is implied that the requirement for complementarity can be paid off with a faster diffusion rate and potentially higher market penetration once the mass audience accepts the idea.

Research on the diffusion of interrelated innovation mostly focuses on the consumer side of the market, where consumers are the sole and dominant decision-makers of adoption and continued usage. Diffusion processes relying on the joint decisions of different social systems receive little attention. One exception is Bucklin and Sengupta (1993b), which discusses a co-diffusion process of complementary innovation in a business-to-business context, namely, supermarket scanners and Universal Product Code (UPC) symbols. The authors define the co-diffusion process as the positive interaction between the demands for the complementary innovations from two separate adopting groups – the manufacturer group and the retailer group. The manufacturers demand UPC symbols to track the shipment, while the retailers demand scanners at the checkout to record sales and thus manage inventory. A positive feedback effect identified between the retailers' demand for scanners and manufacturers' demand for UPC symbols in their empirical study supports this conceptualisation.

4.2.2 Two-sided Markets

The heterogeneity of adopting groups is also addressed in the early work of Rogers (1983). However, only in recent years has research on the diffusion of innovation across segments started to generate fruitful results. By examining the saddles in the diffusion path of innovation, Goldenberg, Libai, and Muller (2002) classify adopters into two separate submarkets given their significantly different adoption rates. Additional examples can be found in Bakshi, Hosanagar, and Bulte (2007) and Niculescu, Shin, and Whang (2012), in which the diffusion process is examined between inherently different consumer segments. While those studies emphasise more on the different characteristics of each segment rather than the interactions between segments that would occur in a two-sided market, it is reasonable to expect that the diffusion of interrelated innovations may also exhibit distinct diffusion patterns across different markets or submarkets.

According to Rochet and Tirole (2002), a market exhibits two-sidedness if its functionality requires getting both sides of the market on board, and the strategies taken by one side of the market influence the decisions made on the other side. An operating system and software, advertising allocation and TV programs, as well as a payment card market, all exhibit this two-sidedness (Evans, 2003). Building on the theoretical base of the two-sided market, a handful of empirical studies investigate the interactions between market participants. Rysman (2004) empirically examines the two-sided market in the context of yellow pages with a positive feedback loop identified between consumers' demand for information on the yellow pages and retailers' demand for viewers attracted by the yellow pages. In a similar vein, Wilbur (2008) examines the viewers' demand for programs and advertisers' demand for viewers in the context of TV advertising. Unlike viewers of yellow pages who will actively search for advertising information, viewers of TV programs are advertisement-averse in general. Especially, the diverse preference of viewers adds to the complexity of modelling the interaction between viewers and advertisers and thus raises the equilibrium of the advertising amount as a result.

Other discussions pertaining to the two-sided markets are around the pricing policies and the strategic competition (Seamans & Zhu, 2014). A skewed pricing structure, commonly called the discriminant pricing policy, is empirically supported in a two-sided market as it accounts for the heterogeneities between the two sides and helps get both sides on board. Optimal pricing policy is further incorporated as a key input of competition evaluation, leading to managerial decisions such as market entry and the choice of market alliance (Arango et al., 2015; Bucklin & Sengupta, 1993a; Danaher, 2002; Weyl, 2010). However, based on our literature review, little research effort has been spent on understanding how innovation diffuses in a two-sided market. Given the structural differences between a two-sided market and a traditional consumer market, the impact of the two sides on innovation diffusion could be different yet not explicitly addressed. The current study, therefore, aims to fill this gap by investigating the joint forces from both sides on the diffusion path of innovation.

4.2.3 Network Effects

The cross-side interaction effects in the two-sided market can be treated as a special case of indirect network effects with the number of participants in the network limited to two. (Parker & Van Alstyne 2005). Literature on network effects builds on the idea of network externalities, originally proposed in Katz & Shapiro (1985) under the terminology of the hardware-software paradigm. Sales of hardware and software are interdependent, with the availability of compatible software affecting consumers' demand for hardware, and the development and launch of software being dependent on the size of the installed base of the hardware platform (Stremersch et al. 2007). As a result, even though the software providers and the hardware manufacturers don't interact directly, their operational decisions are influenced by each other through the consumers' mediation.

Network effects are categorised into direct and indirect effects based on whether the increase in values or sales happened within the same category (hardware and software respectively) or across the different innovations (between hardware and software). In the hardware-software diagram, direct network effect is hardly found in the hardware diffusion (although some platforms encourage social and chat features, these are effectively trivial). In contrast, indirect network effects are found as prominent drivers of the growth, as more hardware users promote the release of more software titles, and this in turn, encourages more hardware uptake (Basu et al., 2003; Gupta et al., 1999; Stremersch et al., 2007).

Nair, Chintagunta, and Dube (2004) measure the size of the indirect network effects via empirically analysing the demand of the personal digital assistant. The authors account for the endogeneity between the hardware sales and software availability by modelling the equilibrium determination of software availability explicitly, rather than through the size of the installed base of the hardware. A positive effect of software variety is found on the hardware demand. Further down this stream, the quality of the software is found influential on the demand for hardware and the magnitude of the impact tends to vary at different stages in the hardware lifetime (Binken & Stremersch, 2009; Gretz et al., 2019).

In a two-sided market context, Rochet and Tirole (2006) modify the idea of network externalities into same-group externalities and cross-group externalities. The authors claim that the same group externalities are mainly due to competition or substitution, while the externalities stemming from the cross groups result from the two-sidedness of the market. Hence, two-sided markets such as platforms are often characterised by indirect network effects (Gretz et al., 2019; Zhu & Iansiti, 2012).

Caillaud & Jullien (2003) document that the indirect network effect in the two-sided market raises the question of "chicken and egg", pointing out a strategic dilemma for the network providers in terms of how to attract both sides on board and which side to target first. By examining the role of exclusivity, the authors suggest that relaxing exclusivity not only enhances the number of users but also mitigates the influence of competition. The results suggest that single-homing users, who partner with only one provider, tend to demonstrate a stronger stance in the market while multi-homing users tend to show a compromised stance with greater willingness to facilitate transactions. In other words, in a two-sided market, the market status of both sides may not be equal, resulting in one side to be more willing to facilitate the transaction by increasing the compatibility for the other side.

The role of exclusivity is further examined in Mantena, Sankaranarayanan, and Viswanathan (2010) through the lens of platform competition. Instead of viewing the market as a mature and static one, the authors offer quantitative analysis on the role of exclusive contracting proposed across different stages of the market and recommend choosing business strategies accordingly. Non-exclusivity is most beneficial at the intermediate stage while exclusivity is preferred during both the nascent and the mature stages. The finding implies that there is dynamics between the two sides as the market evolves and the indirect network effects may shape the power of exclusivity in the market.

Although extensive research has been done for the two-sided markets, prior research largely adopts a static or cross-sectional view of the adoption decisions and thus fails to examine the dynamic interaction between market participants (McIntyre & Srinivasan, 2017). The static view may be appropriate for single-purchased products such as music albums and video games (Zhu & Zhang, 2010). But in the market where the decisions are made for each usage case of service, which is more frequent than decisions for packaged goods, the static view may fail to capture the evolution along the growth. In addition, extant studies assume that only the same-side users can interact with each other and thus incur the direct network effects, evidenced by users of social networks and telecommunication. Third parties mediate the interaction between cross-side users; thus, only the indirect network effect is relevant. Those assumptions tend to discard the necessity of obtaining a dynamic view in a two-sided market, as the interaction between the two sides is deemed either unachievable or negligible.

However, in cases where direct interaction is possible, the frequency and consequences of interaction are increasingly important.

Despite vast research outputs in diffusion of innovation, we are not aware of any work that explicitly examines the innovation diffused co-dependently with direct interaction between the merchant population and the consumer population. While there are many studies of complementary innovation or hardware/software interdependencies, the focal decision makers are consumers. The hardware/software research stream focuses on the network effects describing increases in the values of the network as the result of the increased number of users (Fang et al., 2015), with a consumer-centric approach. The diffusion of related innovations required to be adopted by separate populations has rarely been studied, and the interactions between the related adopting groups require explicit examination. Therefore, the current study aims to fill this research gap by examining how the consumer and merchant groups drive the co-dependent diffusion of innovation and how these two social systems interact over time.

4.3 Study Framework

To achieve the research goal, we coin the concept of co-dependent diffusion of innovation to describe the usage growth of innovation that is jointly dependent on the demand of more than one social system. This concept specifies the diffusion of innovation driven by involved social systems in a two-sided market, which differs from the diffusion of complementary products in a consumer market and the diffusion of information systems in a business-to-business market.

We assume the co-dependency between the two sides is derived from their respective demand for the interrelated innovation. Prior literature on the indirect network effects builds a system of models based on the feedback effect between hardware demand and software supply. That is, the hardware demand is a function of software availability, and the software supply is a function of the hardware installed base (Stremersch et al. 2007). The end-users of both hardware and software are the same group of consumers who are the key decision-makers of what to purchase in the market. Thus, the network effect between the hardware and software providers is mediated by consumers.

In the context of co-dependent innovation, we focus on the demand from two social systems in the market, which may directly interact with each other. The adoption and continued usage of the innovation depend directly on the joint efforts from both sides rather than on the mediated effort through a third-party. Admittedly, there are separate sets of demand and supply within each social system, but we assume the demand will not be bounded by the supply. The changes in the demand may result from the influence of same-side users as well as cross-side users. Therefore, we address the overarching research question as how the demand from both sides of the market shapes the co-dependent diffusion process of innovation and how the driving forces from the two sides change over time. We propose a feedback loop as the underlying mechanism to address the magnitude of the drivers, the symmetry of the influence and the dynamics between the involved social systems. Specifically, we aim to answer the following research questions:

RQ1: Whether there is co-dependency in the diffusion of innovation in a two-sided market?

RQ2: How does diffusion evolve over time at each side of the market as the result of the co-dependency?

We propose that the co-dependency is impacted by the feedback loop, and the cross-group influence tends to dominate the diffusion of co-dependent innovation. The diffusion outcome reflects the joint efforts, which can either encourage or discourage further usage from both sides. As a result, the co-dependency tends to change over time due to the feedback loop between adopting groups.

We adopt aggregate usage as the proxy of demand for the innovation for each side of the market. Usage is measured by the number of distinct merchants or consumers engaged in the platform in a given period. Unlike consumer package goods which have a wide range of intensity of usage based on people's consumption rate and perception of its importance in daily life (Ailawadi & Neslin, 1998), service usage tends to be more consistent and predictable, especially for paid-by-usage service categories. Those categories include payment services, public or shared transportation services and some live-streaming entertainment packages. In addition, the service usage rate contributes to the revenue for services providers (Libai et al., 2009), and thus also reflects the construct of adoption widely used in the literature on the diffusion of innovation. Hence, we find the aggregate usage is a good proxy for the demand for the service and a key factor of managerial interest.

In the co-dependent diffusion process, it is critical to understand which side of the market drives the growth of the innovation. Prior literature in the diffusion of complementary innovation sheds light on this question by suggesting the driving force mainly comes from the growth of the hardware, which constitutes the fundamental base of its complementary part (Dewan et al., 2010). In other words, if the related innovation can be explicitly assigned as primary innovation versus complementary innovation, then the installed base of the primary will be likely to determine the growth of the complementary. Most marketing literature, when discussing the growth of the related innovation, follows the tradition of treating one innovation as the primary and the other as the complementary. This paradigm has been used for decades without being questioned with its suitability in today's technology world. However, some prominent features new to the two-sided markets include high built-in compatibility, increased brand switching and consumer openness to multi-homing with more than one provider. Taking an example from the multi-homing practices, once adopting sharing bike services as a supplementary tool for short-distance commuting, consumers are likely to be equipped with more than one sharing bike app to increase the availability of bikes whenever they need one. Similar circumstances are observed in the food delivery industry and car-hailing industry. Due to the growth of these phenomena, assumptions that assign primary and complementary roles to related innovations seem less justified. For example, hardware is less likely to accurately predict the demand for software as the likelihood of multi-homing in the software industry increases. Thus, the driving forces of the co-dependent diffusion of innovation in a two-sided market context cannot be confidently predicted based on the existing knowledge. To shed light into this area, we form the following expectations regarding the nature, strengthen and symmetry of the driving forces from the involved groups in the co-dependent diffusion of innovation in the following ways:

H1. Consumer usage and merchant usage form a long-run co-dependent relationship to evolve together.

H2. The effect of consumer usage on merchant usage will be greater in magnitude and significance than the effect of merchant usage on the consumer usage in the short run.

H3. The effect of consumer usage on merchant usage will be greater in magnitude and significance than the effect of merchant usage on the consumer usage in the long run.

As innovative services tend to attract high frequency of usage, we expect the feedback loop identified in the co-dependent diffusion of innovation to gradually shape the relative positions of the involved social systems along the diffusion process. As empirically corroborated in the hardware/software paradigm, the demand for software is built on the installed base of compatible hardware, implying that the hardware diffuses prior to the prosperity of software. We may find a similar pattern in our research context as one side leads the uptake, and the other side takes some time to catch up. However, if the intensity of usage grows asymmetrically within each side of the market and different social systems exert divergent impacts on the diffusion path of the innovation, the roles of the two sides could switch at a certain point of time. As the tipping point often arises from dynamic change in the marketplace during new product diffusion, we aim to unveil the tipping point of the usage growth of each side as the result of the dynamic interplay between the two sides.

4.4 Empirical study

4.4.1 Data and Measurement

The current study leverages eight years of weekly contactless payment usage data in the developed western market, provided by a payment network provider with a 70% market share who wishes to stay anonymous. To exclude the volatility incurred by COVID-19, we drop the data from the week that COVID-19 hit the studied country and led to a country-wide lockdown.

With the 429 weeks of data , we use the count of distinct contactless-enabled payment cards used in a particular week to represent consumer usage, assuming that 1) people will stick to one card for most of their daily purchases and only switch to another payment instrument when the chosen instrument does not work and 2) the card attrition due to loss or expiry is negligible compared with the diffusion trend of contactless payment. On the merchant side, each merchant-operating terminal that accepts contactless payment for in-store purchases in a particular week is counted as one merchant usage case. We acknowledge that chain stores may operate multiple terminals, and the decision to turn on or off the contactless payment acceptance function may be made either on store base, or across the whole chain with all terminals under management. However, the chain store impact will not be material given that small and medium-sized businesses are dominant in the market under study, with only 0.4% of total registered enterprises recruiting 100 or more employees (data sourced from the statistical bureau of the studied country). Further we see from the data that the maximum number of terminals operated by a single registered merchant is 99, which is rather negligible compared with 100,000 active terminals in the market.

4.4.2 Model-free Evidence

We summarise the key variable: card diffusion and terminal diffusion, in the tables below, paired with plots representing the trend of the two processes over each year after introducing the innovation.

Variable	Operationalization	Literature support
$Card_t$	Number of distinct cards used in contactless transactions in week t	/
$Terminal_t$	Number of distinct terminals accepting contactless transactions in week t	(Gjika et al., 2019; Mezini & Spaho, 2018)

Table 22 Variables and Measurement

Variable	Min	1st Quantile	Median	Mean	3rd Quantile	Max	Correlation with Card Diffusion
Card Diffusion	33	143,729	773,046	893,457	1,645,505	2,220,417	1
Terminal Diffusion	12	4,153	17,068	19,600	34,858	42,683	0.9951

Table 23 Descriptive Statistics

The plots of the usage pattern over time reveal two insights (Figure 12). First, the two diffusion processes share similar upward trending patterns, with the first two years (i.e., 2012 to 2013) exhibiting minimal growth, followed by a steady gear-up from 2014 to 2018. The high correlation coefficient in the descriptive statistics table also confirms this relationship (Table 23). This feature echoes Rogers' diffusion of innovation theory that the diffusion usually starts with a slow growth rate and only picks up when the mass audience is reached.

The second insight lies in the differences among the general similarities. Although the two processes show similar trends and timeframe, it is observed that the lines of the corresponding year in the two plots diverge temporally in the growth rates after the year 2015. Several factors could lead to the divergence, including the mandatory up-take or churn of a particular industry that shifts the merchant diffusion into a slightly different path. It could also be a lagged effect from one group on the other, a factor we could provide substantive evidence for in the analysis of the following section. It is noted that the drop in usage at the beginning and end of each year is driven by the business closure requirements for public holidays during the Christmas and the New Year period. This affects consumers and merchants equally and thus does not have implications on the hypothesis testing.

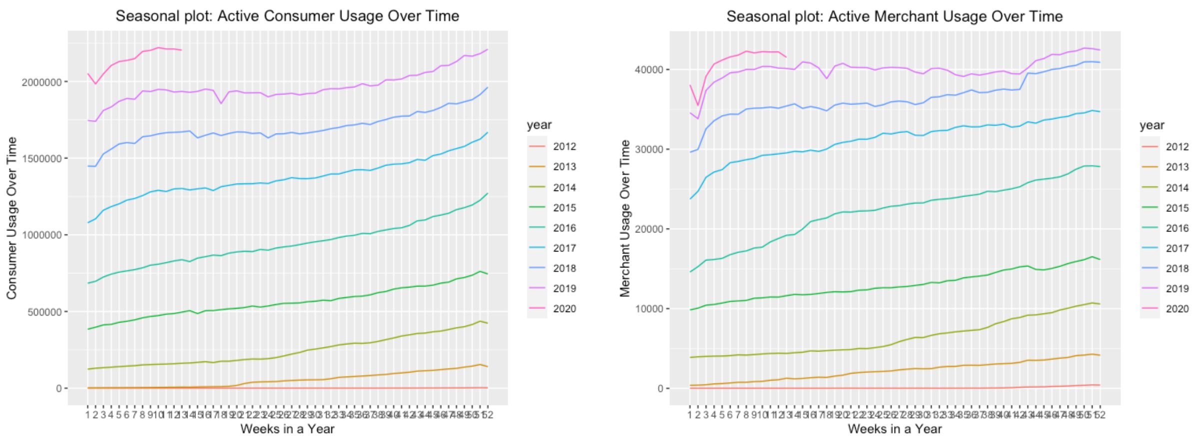


Figure 12 Plots of Active Card Diffusion and Terminal Diffusion Over Year 2012-2020

4.4.3 Methodology

We adopt the Vector Error Correction Model (VECM) to examine the diffusion process of contactless cards and contactless-enabled terminals with the given payment data set. Innovations grow at different rates before reaching equilibrium and the growth rate is found to be impacted by the external communication and the word-of-mouth within the single adopting group (Bass, 1969). When there are two adopting groups in a two-sided market, diffusion paths of co-dependent innovation may co-move or interwind with each other, implying a feedback effect between the adopting groups that shapes the diffusion processes. The economic interpretation of cointegration fits well in this context. Specifically, cointegration can be used to describe the dependent diffusion paths with potential co-movement. Although the each diffusion path may fluctuate due to internal and external factors that drive the diffusion, a large deviation between the two paths is not expected to continue (Wooldridge, 2019). Therefore, the temporal deviation is expected to exhibit the track of reverting to the average level. If the two diffusion paths show divergent trends as time goes by, the innovation may find it hard to thrive in the long run.

One key benefit of applying VECM in the current study lies in the model's capability to account for both short-term and long-term relationships between the two series (processes). VECM treats all variables as endogenous, which is also beneficial as the method avoids restricting the feedback effect to be part of either word-of-mouth influence or external influence dictated in the traditional Bass modelling approach, thereby allowing for more complex interactions to develop. This modelling advantage creates some ease in including dynamic factors in the modelling, which allows the current work to pioneer in providing empirical evidence to understand the dynamics in the diffusion of co-dependent innovation.

We follow the specification proposed in Johansen (1988) to model the card diffusion and terminal diffusion with the following system of equations:

$$\Delta Card_t = \sum_{k}^{K=m-1} \delta_{1k} \Delta Card_{t-k} + \sum_{i}^{I=m-1} \gamma_{1i} \Delta Term_{t-i} + \lambda_1 * ECT_{t-m} + \upsilon_{1t}$$

(Eq1)

$$\Delta Term_t = \sum_{k}^{K=m-1} \delta_{2k} \Delta Card_{t-k} + \sum_{i}^{I=m-1} \gamma_{2i} \Delta Term_{t-i} + \lambda_2 * ECT_{t-m} + \upsilon_{2t}$$

In which,

$$ECT_{t-m} = Card_{t-m} - \alpha - \beta Term_{t-m} \quad \text{(Eq2)}$$

$\lambda_{1,2}$ are derived to understand the speed of adjustment, which is the proxy of the feedback effect resulted from the decision of the other side. To accommodate the long-run mean-reverting speed of adjustment, we include the optimal number of lags (m) instead of the first lag in the error correction term. This specification echoes with the idea that changes in the diffusion level in the most recent period may not be immediately noticeable by adopters on both sides, especially when the applied data set is on a weekly basis. Therefore, adopting the optimal number of lags could better explain the cumulative feedback effect in the long run (Lütkepohl, 2005).

Key steps in the modelling process include:

1. Preliminary data test

We conduct unit root tests – Augmented Dickey-Fuller test (Said & Dickey, 1984) and KPSS test (Kwiatkowski et al., 1992) – to determine the stationarity of card diffusion and terminal diffusion processes. Stationarity in the marketing context indicates that all temporary impacts from marketing mix variables will not permanently change the sales baseline. However, in the diffusion of co-dependent innovation, the stationarity of the two processes is not guaranteed. Any temporary shock from either adopting group may knock the diffusion of innovation into a different track. One scenario can be a sudden regulatory change that requests a sizable portion of users to suspend their usage. Without the participation of the co-working party, it makes little sense for the remaining party to stay in the court, especially when a replacement is handy to switch to. Therefore, a sudden external shock can impact both adopting groups, one via direct restraint on usage and the other via the indirect influence of limited co-working parties. A long-run shift in the diffusion level may loom for the one that suffers a temporary restriction. In the end, the window of diminishing activities of the focal innovation may give competing innovations a chance to catch up and grow their user base. In sum, we are interested in the unit root stationary test results based on the diffusion data, with the expectation that the processes may not be stationary.

2. Optimal lag order selection and Cointegration test

Once proved that the processes are non-stationary but become stationary when differenced, a cointegration test is performed to further examine whether the two processes are cointegrated. The optimal number of lags is selected based on the smallest Schwartz Information Criterion (i.e., SC value). We apply the Johansen cointegration test to the card diffusion and terminal diffusion series. Two tests are used for determining the number of cointegration vectors: trace test statistics and maximum eigenvalue test statistics (Franses, 1994). The current study performs the Johansen test with both types to confirm the number of cointegration relationships.

3. Estimation of VECM

We estimate the VECM specified as Eq (1) with Maximum Likelihood Estimation (MLE). Alternative estimation method can be the Engle-Granger two step approach (2OLS), which requires the β in the ECT to be known forehand (Juselius, 2006). As we expect the β to be estimated with bootstrapping method in our model, we opt for MLE. In the process, we arbitrarily assign card diffusion as the "dependent variable", which helps the interpretation of the results. Mean Absolute Percentage Error (MAPE) and RMSE are reported for the model fit.

4. Examine and interpret the Impulse Response Functions

As Dekimpe & Hanssens (1996) summarise in their work, Vector Autoregressive (VAR) Model and Vector Error Correction Model (VECM) share the common advantages of accounting for the dynamics among the processes; however, those type of models suffer from difficulty in interpreting the parameters. In line with the literature, we derive the associated Impulse Response Functions (IRF) to depict the short-term and long-term effects brought by one unit shock of one process to the other. As for whether the short-run effect shall be interpreted on period zero or period one, literature suggests that the frequency of the data shall be a determining reason for short-term effect interpretation (Ronayne, 2011). If annual data is used, the short-term effect is likely to be based on year zero. On the contrary, if daily or weekly data is used, it appears be more realistic to interpret short-term effect at period one. Therefore, in the current study, we define the short-term effect as the response at period one, and the long-term effect as the cumulative effect after period one till the end of specified number of periods ahead. 95% confidence interval is adopted, and the number of periods ahead is set at 12 (i.e., 12 weeks), matching the nature of data in use.

4.5 Results

Based on the results of the Unit Root Tests (i.e., the ADF test and the KPSS test), we confirm that the two diffusion processes are not $I(0)$ stationary (refer to Table 24~28). Additional Unit Root Tests are performed on the first-differenced processes, showing stationarity for both processes (refer to Table 29). Therefore, the diffusion processes are proved to be suitable for cointegration analysis and move forward to conducting the Johansen cointegration test with the two $I(0)$ processes.

Tables of Augmented Dickey-Fuller Unit Root Test with Diffusion Data (model selection based on "BIC")

	Max.Lags	Method	Tau3| 5%cr.*	Phi2| 5%cr.*	Phi3| 5%cr.*	Conclusion
Card Diffusion	17	Trend	-3.16|-3.42	14.91|4.71	6.33|6.30	Non-stationary
Terminal Diffusion	17	Trend	-2.44|-3.42	6.83 |4.71	2.99|6.30	Non-stationary

Table 24 ADF Test Method = "Trend"

	Max.Lags	Method	Tau2| 5%cr.*	Phi1| 5%cr.*	Conclusion
Card Diffusion	17	Drift	1.16|-2.87	16.30|4.61	Non-stationary
Terminal Diffusion	17	Drift	-0.24|-2.87	7.21 |4.61	Non-stationary

Table 25 ADF Test Method = "Drift

	Max.Lags	Method	Tau3| 5%cr.*	Conclusion
Card Diffusion	17	None	4.98|-1.95	Non-stationary
Terminal Diffusion	17	None	2.87|-1.95	Non-stationary

Table 26 ADF Test Method = "None"

Note: cr.* The critical values are taken from Hamilton (1994) and Dickey & Fuller (1981)

Tables of KPSS Test Results

	KPSS Trend Statistics	Truncated Lags	p-value	Conclusion
Card diffusion	0.44	17	0.01	Non-stationary
Terminal diffusion	0.31	17	0.01	Non-stationary

Table 27 Trend Stationarity with Diffusion Data

	KPSS Level Statistics	Truncated Lags	p-value	Conclusion
Card diffusion	2.47	17	0.01	Non-stationary
Terminal diffusion	2.474	17	0.01	Non-stationary

Table 28 Level Stationarity with Diffusion Data

	Dickey-Fuller	Lag order	p-value	Conclusion
Card diffusion	-10.096	7	0.01	Stationary
Terminal diffusion	-9.5185	7	0.01	Stationary

Table 29 ADF Test with First-order Differenced Data

Results of the Johansen procedure reject the null hypothesis that no cointegrating vector found in the tested processes and thus indicate a cointegration relationship between consumer usage and merchant usage. The cointegration is reasonably strong as the test statistic (65.23) is much larger than the critical value (24.6) at 1% significant level. A constant is included in the Eq(2), which can be absorbed into the cointegration relation as an intercept (Lütkepohl, 2005). This manipulation can be explained by the fact that the success of co-dependent innovation cannot happen simultaneously in thin air – there will be one party making the first move. The first movers, therefore, attract the other side of users to take up the innovation, resulting in subsequent uptakes among non-users to kick-start the interaction process. An argument can be made around how card diffusion can take place when there are no merchants adopting contactless accepting terminals in the market. We refer to the literature about innovation introduced with free-trial opportunities (i.e., Datta, Foubert, and van Heerde 2015). Innovators are invited to try out the new product or service, and the try-out can spread to a wider not-yet-invited group given positive word of mouth. Even though the free trial does not guarantee a lasting relationship between the users and the providers, the trial opportunity helps to increase awareness of the innovation at the introduction stage (Datta et al., 2015; Foubert & Gijsbrechts, 2016). This awareness could be a kicking-off force for co-dependent innovation, as awareness contributes to social contagion and thus boost diffusion at an early stage (Iyengar et al., 2011).

Details of the Johansen Cointegration Test are summarised as follows.

Table of Johansen Cointegration Testing Summary

Johansen Procedure				
Test type:	Trace statistic, without linear trend and constant in cointegration			
Eigenvalues:	1.347886e-01	8.313745e-03	-7.084575e-17	
Values of test statistic and critical values of test:				
Max. cointegration relations	Test	10pct	5pct	1pct
r <= 1	3.56	7.52	9.24	12.97
r = 0	65.23	17.85	19.96	24.6
Eigen vectors, normalized to first column:				
	Card_diffusion.l3	Terminal_diffusion.l3	Constant	
Card_diffusion.l3	1	1	1	
Terminal_diffusion.l3	-59.33	430.00	-48.3162	
Constant	-130601.30	-12103540	64853.68	
Weights W:	This is the loading matrix			
	Card_diffusion.l3	Terminal_diffusion.l3	Constant	
Card_diffusion.d	-0.0210	6.378459e-07	-2.781785e-17	
Terminal_diffusion.d	-0.0005	-3.202841e-06	3.080714e-18	

Table 30 Johansen Cointegration Test Summary

Building on the largest eigenvalue and the corresponding eigenvectors, we construct the Error Correction Model (ECM) as follow:

$$ECT_{t-3} = Card_{t-3} - 7.997 * Term_{t-3} - 17591.995 \qquad \text{(Eq3)}$$

As noted earlier, MLE is adopted for estimating the VECM. Unlike OLS estimation of linear regression or the output of logistic regression, it makes little sense to interpret every parameter estimate from VECM output. However, it is worth examining the sign and the magnitude of $\lambda_{1,2}$ as having one convergent cointegration relation, the $\lambda_{1,2}$ shall be negative. Otherwise, any deviation from the equilibrium between the two processes will not diminish over time and thus the equilibrium will not hold as time passes by. The outputs show negative $\lambda_{1,2}$ values which assure the equilibrium reverting nature in the cointegrating relationship of card and terminal diffusion. Further, we note that the equilibrium deviation has a larger impact on card diffusion than on terminal diffusion (λ_1=0.0209, λ_2= 0.0005, $p<0.01$), indicating consumers are more sensitive towards changes in the prior diffusion process.

<u>Table of VECM Model Output</u>

VECM output					
Full sample size:	429	End sample size:	426		
Number of variables:	2	Number of estimated slope parameters: 10			
AIC: 13296.51	BIC: 13341.11	SSR: 196432519662			
Cointegrating vector (estimated by ML):					
	Card_diffusion	Terminal_diffusion	Constant		
r1	1	-59.33	-130601.3		
Parameter estimates:					
	ECT	Card_ Diffusion.d1	Terminal_ Diffusion.d1	Card_ Diffusion.d2	Terminal_ Diffusion.d2
Equation card_diffusion	-0.0209 (0.0026)***[8]	-0.8682 (0.0932)***	30.3373 (3.4835)***	-0.6141 (0.0997)***	14.8654 (3.7744)***
Equation terminal_diffusion	-0.0005 (6.6e-05)***	-0.0217 (0.0024)***	0.7764 (0.0887)***	-0.0160 (0.0025)***	0.2164 (0.0961)*

Table 31 VECM Output Summary

Based on the model output, we provide answers to the proposed hypothesis in the following table (Table 32). All hypotheses are supported with the empirical output.

[8] *** p<0.001; ** p < 0.01, * p < 0.05

H2. The effect of consumer usage on merchant usage will be greater in magnitude and significance than the effect of merchant usage on the consumer usage in the short run.

H3. The effect of consumer usage on merchant usage will be greater in magnitude and significance than the effect of merchant usage on the consumer usage in the long run.

	Hypothesis	Results	Support?
H1	There is co-dependent relationship between consumer usage and merchant usage.	Confirmed cointegration relationship with r=1	Yes
H2	The effect of consumer usage on merchant usage will be greater in magnitude and significance than the effect of merchant usage on the consumer usage in the short run.	IRF shows an increasing and significant response for consumers usage. Although an immediate response is observed in merchant usage, the response becomes insignificant quickly in the coming weeks.	Yes
H3	The effect of consumer usage on merchant usage will be greater in magnitude and significance than the effect of merchant usage on the consumer usage in the long run.	$\lambda_1 > \lambda_2$ in the VECM output, indicating a higher adjustment for consumer in case of long run deviation from equilibrium. The conclusion is also corroborated in the IRF for predictions in the long run.	Yes

Table 32 Summary of Hypothesis and Findings

The following table reports the predictive fit of the model. We adopt correlation coefficient, MAPE and RMSE as the diagnostic measurement and calculate the corresponding values between the fitted, actual, and predicted values. The model estimated with full data available before COVID-19 hit the studied country fits the data very well, evidenced by high correlation coefficient between the fitted values and the actual data, and low MAPE and low RMSE per measurement. Using around 75% data for training and the remaining 25% for validation, the diagnostics show sound predictive power. While the correlation coefficients decrease for consumer and merchant processes with out-of-sample data, the out-of-sample MAPE and RMSE remain reasonably low. The decreased correlation coefficients may be due to the inclusion of end of year holiday season featured with 2 mandatory store closing days. Collectively, we conclude that the predictive fit of the model is satisfactory.

	Fitted Process (n=426, full data)			Predicted Process (n=108, out-of-sample data)		
	Correlation Coefficient (r)	MAPE	RMSE	Correlation Coefficient (r)	MAPE	RMSE

Card Diffusion	0.9996 (p<0.001)	1.4830	21,466.5	0.9627 (p<0.001)	0.1180	266,825.1
Terminal Diffusion	0.9993 (p<0.001)	0.3360	546.5	0.7998 (p<0.001)	0.1396	6,917.93

Table 33 Model Diagnostic Summary

<u>Figure of Prediction of Card Diffusion and Terminal Diffusion with Training data</u>

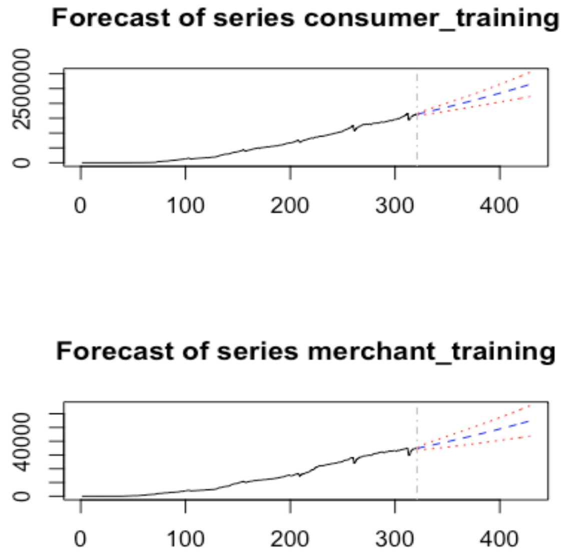
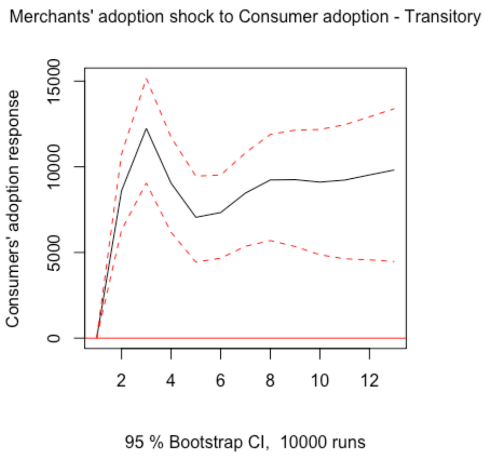
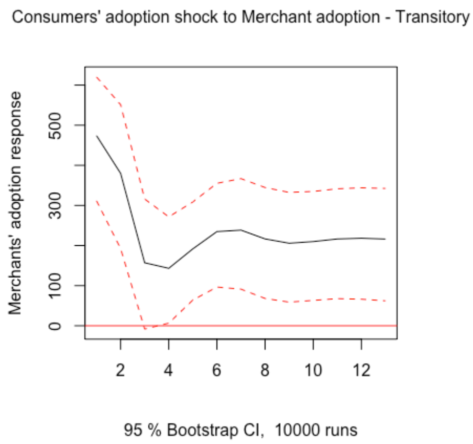


Figure 13 Plots of Model Forecasting

In line with the literature, we focus on the impulse response functions associated with the VECM to understand the interaction between the cointegrated processes in the short term and long run (Dekimpe & Hanssens, 1996). Impulse response functions help trace the impacts of one unit change in one variable on the other variable for specified periods. As shown in the following Figure 14, in Plot (A), a shock in terminal diffusion will incur short-term boost to card diffusion, as more merchants configuring their contactless-enabled terminals at the checkout will encourage consumers to pay contactless with their cards. Likewise, a shock in the card diffusion will positively impact terminal diffusion, evidenced by a significant merchant response (i.e., Plot (B)). However, the impact in the subsequent periods diverge between card and terminal diffusion. Merchants' shock keeps inspiring consumers' usage in the first two weeks, which peaks in the third week before dropping to a more stabilized level in the following weeks. The impact is deemed lasting, supporting the argument that a shock in contactless terminal usage will have positive impacts on contactless card usage for about 3 months (i.e., 12 weeks). On the contrary, consumers' usage shock exhibits a diminishing positive impact on merchants' usage, even briefly falling into no impact area on week 3 as the confidence interval touches zero, and then bounces to a moderate impact in the following 8 weeks. Figure 15 confirms the pattern with 24 weeks' forecast ahead.

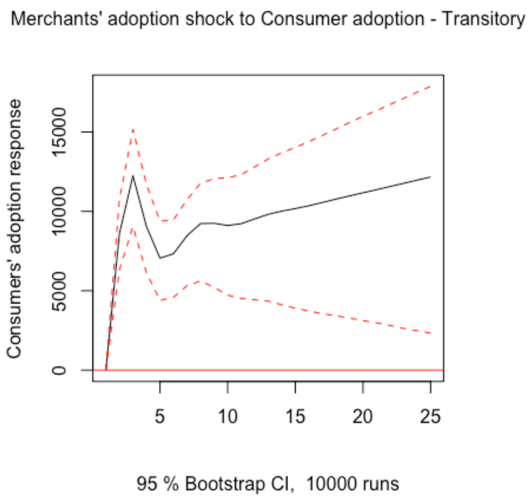


Plot A

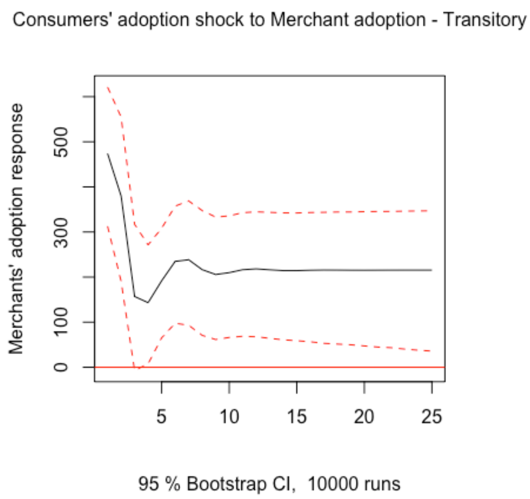


Plot B

Figure 14 Impulse Response Functions (n.ahead = 12 weeks, cumulative = FALSE)



Plot A



Plot B

Figure 15 Impulse Response Functions (n.ahead = 24 weeks, cumulative = FALSE)

Results summary

In sum, the results confirm a cointegration relationship between merchant usage and consumer usage, and consumer usage appears to be more sensitive (i.e., greater in magnitude and significance) to the variation of co-dependent diffusion in the market. A shock in merchant usage positively impacts consumer usage in both the short run and the long run. The response function, unlike marketing mix impacts that tend to converge to zero in the long run, exhibits a permanent change to the diffusion path of co-dependent innovations. This observation resonates with the importance of leveraging the interaction between the two adopting groups in the diffusion process of co-dependent innovation.

4.6 Robustness Tests

To test the robustness of the results, we re-run the whole modelling with bi-weekly data. We expect that the data frequency will not impact the cointegration relationship between the card diffusion and terminal diffusion. In addition, we expect the short-term and long-term effect given one shock from one process to the other will be maintained. We acknowledge the fact that the optimal number of lags shall be reduced with the bi-weekly data, therefore parameters will not be identical. Results from Table 34 & 35 and Figure 15 confirm that all the key findings sustain with the bi-weekly data and thus the general conclusions stay the same.

Tables of Robustness Test with Bi-weekly Data

Johansen Cointegration Test

Johansen Procedure				
Test type:	Trace statistic, without linear trend and constant in cointegration			
Eigenvalues:	2.491538e-01	1.270696e-02	-5.969546e-17	
Values of test statistic and critical values of test:				
Max. cointegration relations	Test	10pct	5pct	1pct
r <= 1	2.71	7.52	9.24	12.97
r = 0	63.46	17.85	19.96	24.6
Eigen vectors, normalised to first column:				
	Card_diffusion.l2	Terminal_diffusion.l2	Constant	
Card_diffusion.l2	1	1	1	
Terminal_diffusion.l2	-91.20	-65.8982	-54.19009	
Constant	-939230.10	278479.1076	-20189.05902	
Weights W:	This is the loading matrix			
	Card_diffusion.l3	Terminal_diffusion.l3	Constant	
Card_diffusion.d	-0.0115	0.002335	2.619398e-16	
Terminal_diffusion.d	-0.0002	0.000295	1.130645e-17	

Table 34 Robustness Test -- Johansen Cointegration Test

VECM output			
Full sample size:	214	End sample size:	212
Number of variables:	2	Number of estimated slope parameters: 6	
AIC: 6930.41	BIC: 6953.90	SSR: 220565662663	
Cointegrating vector (estimated by ML):			
	Card_diffusion	Terminal_diffusion	Constant
r1	1	-91.20403	-939230.1
Parameter estimates:			
	ECT	Card_ Diffusion.d1	Terminal_ Diffusion.d1
Equation card_diffusion	-0.0115 (0.0014)***	-0.9309 (0.1435)***	26.4981 (5.4410)***
Equation terminal_diffusion	-0.0002(3.5e-05)***	-0.0261 (0.0036)***	0.6179 (0.1364)***

Table 35 Robustness Test -- VECM Output

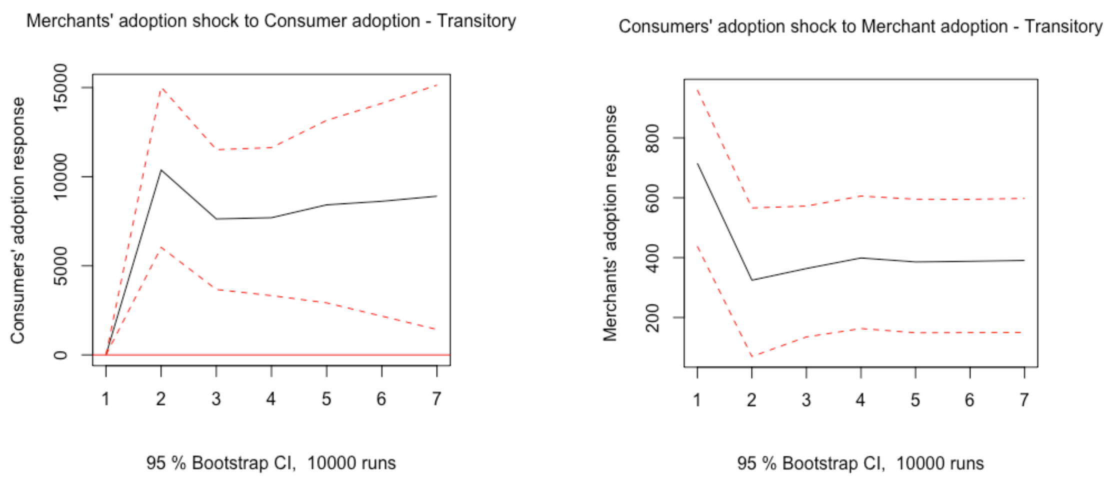


Figure 16 Robustness Test – Impulse Response Function with Bi-weekly Data

4.7 Rolling Window Examination

Empowered by the rich data set, we further study the cointegration relation through different periods. The diffusion of innovation tends to exhibit an S-shaped path, indicating changing adoption rates at different levels of innovation penetration. As time goes by, the magnitude of the effect within the social system may change, and so may the effect of the interaction between the co-dependent social systems. So, although our main study helps to explain the pattern between consumer usage and merchant usage in both the short-term and long-run, we wonder whether slicing the data into three windows will illustrate different patterns. Therefore, we set up 3 moving windows for the 8 years of data (i.e., from 2012 to

2019), each with 156 observations, covering three full years from January to December. Moving window analysis helps to leverage data from the different time period with the same sample size, enabling direct comparison of the results (Pauwels & Hanssens, 2007).

Two follow-up questions are expected to be answered with this exercise. So far, it is unclear whether the cointegrating relationship between consumer and merchant usage consistently presents over the whole 8 years. If the presence is confirmed, how does the strength of the interaction tend to change? Will the interaction be enhanced, be stable or be declining as diffusion reaches a higher level of penetration? Those questions regarding the existence of dynamic interaction and the changes of the interaction direct our focus to the results of the Johansen cointegration test, the magnitude of $\lambda_{1,2}$ and the shape of the IRF.

Data plots per moving windows are shown in Appendix E Figure 1 followed by IRF results in Appendix E Figure 2. Results confirm the cointegration between consumer usage and merchant usage over time, but a clear pattern of declining relevance is spotted. Card and terminal diffusion in the first four years, namely from 2012 to 2016, align in all three aspects with our focal discussion in prior paragraphs (i.e., the existence of cointegration relationship, the relative magnitude of $\lambda_{1,2}$ and the shape of the IRF). However, in recent years, both the cointegration and the response functions upon shock indicate that the consumer usage and merchant usage become less relevant to each other. This result implies the early stage of diffusion a critical for the success of diffusion as the diffusion outcome depends highly on the interaction of the two adopting groups.

It may go against the common wisdom that the interaction between adopting groups will become stronger and more self-driven when there are enough users on both sides of the market. Network effects are expected when the user base is enlarged and greater benefit is associated (Katz & Shapiro, 1986). It may be natural to assume that larger network effects lead to more effective interaction among adopting groups and thus further drive growth. However, as Goldenberg, Libai, and Muller (2010) suggested in their work, network externalities exert a substantive effect on the diffusion path mainly in the early stage of diffusion. Our findings provide a potential explanation for this slowing down phenomenon, via the interaction between adopting groups. Interaction should be facilitated as early as possible, as when each side of the market has grown a large user base, the actions taken by the opposite side appear to have a diminishing impact on the usage decision of the current side. The diffusion rates and the penetration of the innovation are therefore plateaued as the feedback effects diminish. A summary of the results is presented in the following table.

	2012-2014			2014-2016			2017-2019		
	Co-integration relationship	Response to long-run deviation	IRF	Co-integration relationship	Response to long-run deviation	IRF	Co-integration relationship	Response to long-run deviation	IRF
Card Diffusion	Strong	-0.0128 (p<0.001)	Similar	Strong	-0.0148 (p<0.001)	Similar	Marginal	0.0101 (p<0.001)	Differ
Terminal Diffusion		-0.0003 (p<0.001)	Similar		-0.0003 (p<0.001)	Differ		0.0002 (p<0.001)	Differ

Table 36 Rolling Window Modelling Summary

4.8 Discussion of Findings and Implications

Innovations that rely on the interactions between adopting groups are growing rapidly in the market. Unlike typical examples of two-sided markets where the market organisers (i.e., platform operators) have great power in pricing and regulating the involved parties, co-dependent innovations diffuse based on the adopting groups and the interaction between them. A strongly mediated platform-based market tends to lay out separate pricing or promotional strategies on each side (Evans, 2009), leading to one side becoming more favoured than other side(s). However, promoting on one side could incur undesired outcome if the promotion terminates and the favourable terms are no longer offered. Users attracted by free-trial promotions show a higher churn rate compared to regular users can be viewed as one example (Datta et al., 2015). Therefore, encouraging engagement and interaction is essential for two-sided service markets, as the driving forces of growth as well as the profits come from the size of adopting groups and the continued usage of the service provided. Given the gap in the literature, there comes a pressing need for market organisers to understand how co-dependent innovation evolves before laying out strategies to leverage the momentum between the adopting groups. Researchers who draw on the current knowledge of diffusion of innovation, economics in the two-sided markets and network effects risk underplaying the importance of the interaction between the adopting groups by not directly estimating the impact of interaction and its dynamics.

The current study tests the co-dependency in adopting groups for co-dependent innovation. The relationship between the adopting groups involved in the diffusion of related innovation has been assumed rather been tested in prior literature. The Unit Root Test and Johansen Cointegration Test results confirm the co-integrated relationship between card diffusion and terminal diffusion, indicating a co-dependency between consumers and merchants in their decision making of adopting and utilising the co-dependent innovations.

According to Juselius (2006), the interpretation of estimated coefficients from a dynamic model is usually less straightforward than the ones from a static regression output. Therefore, Impulse Response Functions (IRFs) are used to understand how merchant usage and consumer usage interact. IRFs are means of measuring the influence of one variable in the VAR or VECM system on the other variable(s). Given one "shock" in consumer usage (merchant usage) at time zero, the IRFs represent the response of merchant usage (consumer usage) in the subsequent periods. Based on the IRFs, we conclude that in the short term, shock from merchants' usage positively impacts consumers' usage, and the impact grows in the long run. The impact of one shock from consumers' usage, though immediate and positive, tends to drop quickly in the short term. As for the long run, we see both processes translate the one-unit shock into a permanent lift.

As an indicator of the speed of adjustment, the size of lambdas provides information about how sensitive adopting groups are towards the diffusion deviated from the long-run equilibrium. The estimated lambdas show that the speed of adjustment for consumer usage is larger than that for merchant usage. Consumers tend to be more sensitive, and show greater magnitude and significance in response, given the diffusion outcome of co-dependent innovation. This finding contradicts the common wisdom that merchants who bear the cost of accepting contactless payment are expected to be more sensitive about whether the consumers appreciate their acceptance of contactless payment or not. According to the results, merchants tend to have higher tolerance even if the diffusion level fails to meet the expectation.

As for the magnitude of the dependency, we find it gets stronger in earlier years and dissipates in recent periods even though the innovation still grows. This finding goes against the logic in the network effect theory, in which larger user bases tend to show stronger direct network effects (Stremersch et al., 2007). In the video game industry, the supply of game titles depends on the installed base of compatible game consoles, resulting in more console purchase leading to more game titles being supplied in the market. This relationship is deemed as a manifestation of indirect network effect (Stremersch et al., 2007). Our results present declining interaction effects between adopting groups when there are more users in both sides, and even when users tend to use the innovation more often. This change of dependency may be explained by the possibility that consumers are generally less motivated to learn about other brands or methods after they have settled on a satisfactory choice (Bronnenberg et al., 2000). This satisfactory settlement could be enhanced in the co-dependent innovation circumstance, where the required adoption and usage from the other side of the market provide more certainties for using this innovation. Therefore, as diffusion reaches a certain level, the interaction between adopting groups shows diminishing marginal benefits. It may become "business as usual" for users to engage in co-dependent innovation as the result of the action out of habit. Any deviation from expectation, such as encountering a merchant who does not accept contactless payment, will not cause consumers to doubt their choice of the payment method. They may still try paying contactless next time at another merchant.

Theoretical implications

We contribute to the extant literature on two-sided markets and service diffusion. First, the current study explicitly accounts for the diffusion of innovation that builds on the demand from more than one social system in a two-sided market. Specifically, we examine the magnitude and dynamics of the interaction effects between the adopting groups in a two-sided market. Interaction-based cooperation is required for co-dependent innovations to thrive in this context. Prior literature that examines the interaction of multiple players in the market resorts to the hardware-software paradigm. Although the hardware-software paradigm provides the context that pairs the consumers' demand for hardware to the level of supply of the software, the interaction between hardware providers and software complementors is both mediated by the consumers. In the context of the co-dependent diffusion of innovation, we find that the respective demand from both the consumer and merchant side of the market jointly impacts the diffusion path, and the impact is asymmetric, with consumer side being more responsive to changes in the diffusion.

Second, to our best knowledge, we are among the first to examine usage-based adoption in service diffusion modelling. Chandrasekaran and Tellis (2015), in their critical review of diffusion literature, urgently call for expanding the research from consumer durables to other categories such as services and agricultural products. Consumer durables and consumer electronics are most frequently examined in diffusion studies, owning to the availability of sales data and the variation of sales growth among successive generations. In contrast, the usage case of service diffusion has received less attention, attributing to the insufficient usage data. However, the importance of service research has surged in recent years as more products transform into subscription-based services (i.e., Software as a Service) and more services lay out their pricing plans, including recurring subscriptions and pay-by-usage rates. Unlike consumer durables purchase when much thinking is given to the one-time purchasing decision, consumers may opt services out of habit, which is likely to result from the frequent usage case that increases the automation of behaviour and lowers the consciousness of intention (Markus & De Guinea, 2009). Therefore, the measurement of adoption – by initial purchase versus by usage – distinguishes the diffusion of services from that of consumer goods, where the service diffusion is the theoretical and empirical focus of the current study. Results present the pattern of co-dependent innovation diffusion in the service setting based on the weekly number of usage cases of each adopting group. The diffusion of the co-dependent innovations consists of the initial adoption as the result of advertising and word-of-mouth communication, the short-term usage fluctuation from both sides, and the deviation from long-run equilibrium.

Methodological implications

Diffusion data shows a strong association with time. In fact, the classic Bass Model (Bass, 1969) builds solely on the sales outcome and the passage of time. Studies from multiple disciplines base their analysis on the Bass Model, with various modifications and adjustments, such as including exogenous variables, changing the estimation methods, and leveraging data from different industries and different countries, to help answer specific questions (refer to Chandrasekaran & Tellis (2015) for a summary on the main generalizations of Bass model). However, among the rich diffusion modelling literature, time series methods see limited usage. The current study provides an application of VECM to the diffusion data. The VECM model not only examines the dynamics in the diffusion process, but also demonstrates the interactions between adopting groups. Prior diffusion work trying to depict the interactions between separate adopting groups or adopting segments within one group often needs to set up assumptions at the beginning. Those assumptions may include which group or segment shall take up the innovation first, how to incorporate the interaction effect between groups or segments in the classic Bass Model and what is the proper estimation approach (Goldenberg et al., 2002). As the diffusion of co-dependent innovation is novel with many unknowns, specifying the model right at front is challenging and could lead to bias. VAR and VECM models provide the flexibility of letting the data tells how to configure the model. Moreover, if the adopting groups are expected to interact, cointegration test can shed light on how many processes are cointegrated and what those are exactly. Then, VECM can be a good candidate to provide insight on short-term and long-term patterns. With more platform-type markets relying on a certain level of cooperation from more than one adopting group, we expect more time series models shall prove to be useful in understanding both innovation diffusion and the adopting groups' interaction.

Managerial Implications

An important consideration from the managerial point of view is to understand how merchant usage and consumer usage evolve as the result of the interaction between the two sides. The stationary nature of the process indicates that all temporary changes, such as temporary price promotions, will not lead to permanent increases in sales (Fok et al., 2006). In contrast, the findings about the cointegrating relationship between consumer usage and merchant usage substantiate that a shock on either side of the market can stimulate diffusion. If market organisers struggle to understand the appropriate strategies for a two-sided market and which side they should focus on first, our findings at least point in a clear direction. The key to co-dependent innovation's success is enhancing interaction at an early stage. As long as the two processes show co-integration, an easy push shall get the ball rolling, triggering an enhanced feedback effect that leads to a permanent lift.

Providers can also leverage the momentum between the adopting groups based on the knowledge of the changing dynamics of adopting groups over time. Prior research emphasises the characteristics of the innovation and demographics of the adopting groups with a static point of view. Little research has been conducted on co-moved diffusion paths and the dynamics along such diffusion processes. Given that the interaction between the two sides could foster momentum in the usage outcome, our modelling results show that the responsiveness of each side towards the action from the other side and towards the diffusion level in the market could differ. For instance, merchants are found with a surging response in the short term, and consumers are found to be more responsive to changes in usage in the long run.

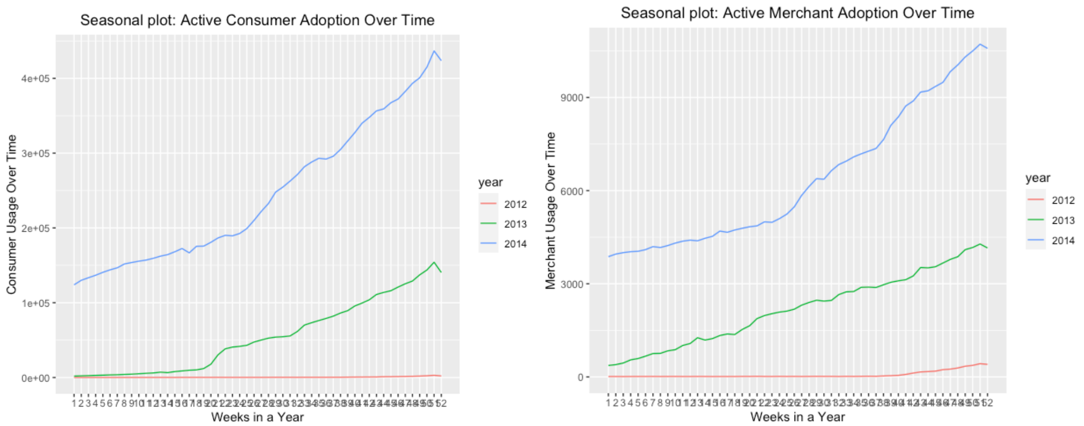
4.9 Limitations and Suggestions for Future Research

Due to the data availability, the current study only examines one type of co-dependent innovation diffused in one developed economy. Literature proves that country characteristics and cultural differences could also contribute to the divergent diffusion paths of similar innovation products (Dewan et al., 2010; Putsis et al., 1997). Dekimpe et al., (2000) examine the global diffusion of technology, indicating that country wealth positively relates to technological product diffusion, and so does the country’s prior experience with that innovation. Therefore, it would be interesting to examine the diffusion pattern of contactless payment innovation across a group of countries, with different levels of economic development and different ideologies of potential adopters.

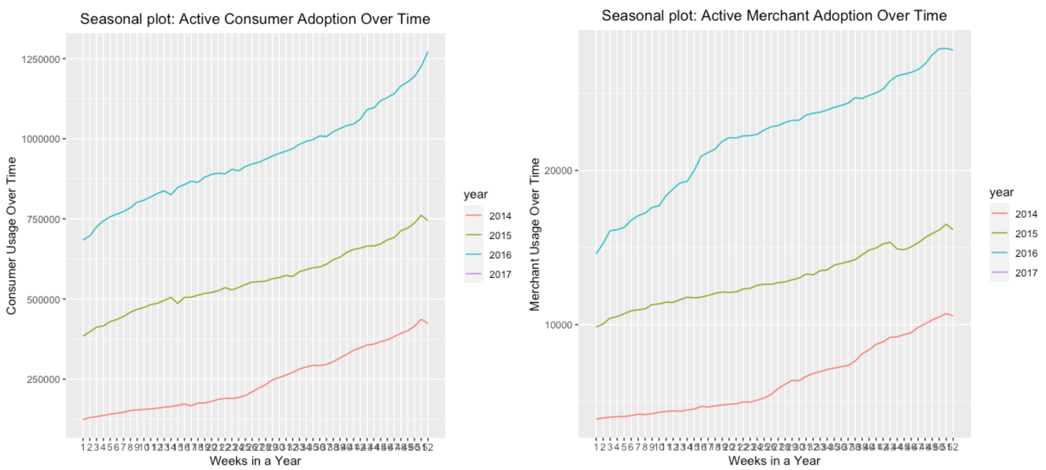
Appendix E Moving Window Results

Figure 1 Model-free evidence – Moving Window Data Plot

Year 2012-2014 Consumer Usage vs. Merchant Usage



Year 2014-2016 Consumer Usage vs. Merchant Usage



Year 2017-2019 Consumer Usage vs. Merchant Usage

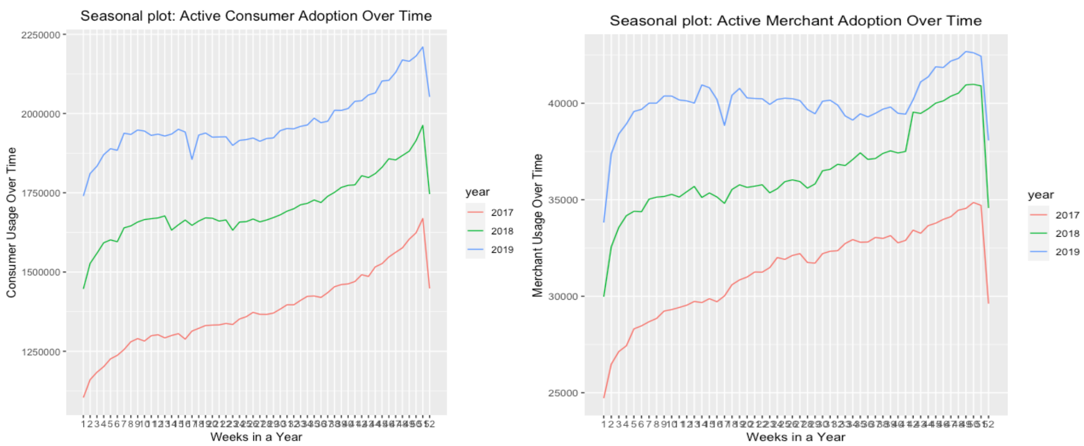
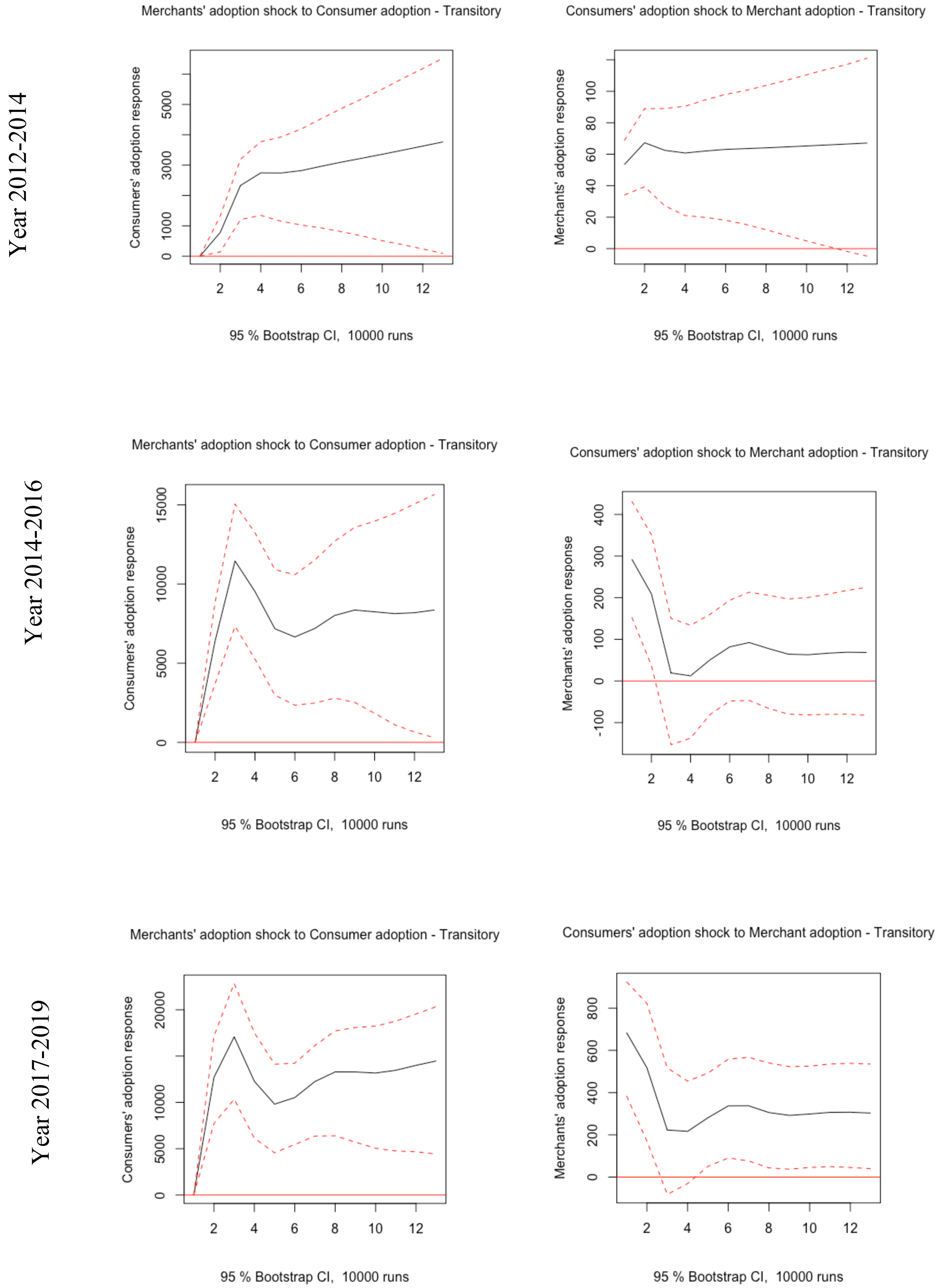


Figure 2 Impulse Response Functions based on Moving Windows



Appendix F Statement of Contribution

DRC 16

MASSEY UNIVERSITY
TE KUNENGA KI PŪREHUROA
UNIVERSITY OF NEW ZEALAND

GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Xing (Alison) Chen
Name/title of Primary Supervisor:	Prof. Malcolm J. Wright
In which chapter is the manuscript /published work:	Chapter 4

Please select one of the following three options:

○ The manuscript/published work is published or in press

- Please provide the full reference of the Research Output:

○ The manuscript is currently under review for publication – please indicate:

- The name of the journal:
- The percentage of the manuscript/published work that was contributed by the candidate: 60.00
- Describe the contribution that the candidate has made to the manuscript/published work:

The candidate completed the research design, literature review, model specification, analysis and writing. The role of the supervisors has been restricted to assisting with the conceptualisation of the project, advisory comments on research design and analysis, and critical evaluation and editorial comments on written drafts.

● It is intended that the manuscript will be published, but it has not yet been submitted to a journal

Candidate's Signature:	Xing Chen Digitally signed by Xing Chen Date: 2022.09.17 23:34:25 +12'00'
Date:	17-Sep-2022
Primary Supervisor's Signature:	Wright, Malcolm Digitally signed by Wright, Malcolm Date: 2022.09.18 11:39:30 +12'00'
Date:	18-Sep-2022

This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis.

GRS Version 5 – 13 December 2019
DRC 19/09/10

Chapter 5 Conclusion and Future Directions

The goal of this thesis is to gain understanding of the diffusion of a newly identified type of innovation – co-dependent innovation – in two-sided markets. The co-dependent innovations rely on more than one adopting group to function and therefore the diffusion pattern may be influenced by the interaction between the adopting groups. However, prior literature fails to clearly define this type of innovation and thus no modelling framework is dedicated to understanding how co-dependent innovation diffuses. The growing number of innovations featured with co-dependency, such as the payment method innovation and the electric vehicles, poses an urgent need to understand how co-dependent innovation grows at the aggregate level over time.

In section 5.1 we present the key findings from Chapter 2 to Chapter 4 and address the research questions proposed at the opening section of the thesis. We then discuss the theoretical contribution in section 5.2 and offer the managerial implications that can be leveraged by managers to boost the diffusion process of co-dependent innovation in section 5.3. The thesis concludes with a discussion on the limitations and highlights the directions for future research.

5.1 Summary of Key Findings

In Chapter 2, we attempt to replicate the mechanisms proven in the relevant literature to understand whether prior mechanisms can be used to explain the diffusion of co-dependent innovation. Three promising modelling frameworks are selected as the target for the differentiated replication, namely the multi-product Bass model in Bucklin and Sengupta (1993b), the indirect network effect tested with a nonlinear system of equations in Stremersch et al. (2007) and the influx and outflow model for two-sided markets in Hinz et al. (2020). We fail to fully replicate any of the proven mechanisms with payment data. Although the Bass model with independent innovation specification works well for both merchant usage and consumer usage, the interaction models account for the co-diffusion effect fail on both merchant and consumer ends. Our replication results show significant same-side and cross-side effects for merchant and consumer usage, which differ from Stremersch and his colleagues' conclusion that indirect network effects are rare and marginal. Only two out of eight relationships between the existing users in the two-sided market and the influx and outflow of users on each side are replicated with payment data. Results show that the co-dependent diffusion of innovation implies cooperation instead of competition on the same side and across sides, therefore only the cross-side enhancement is found significant in the replication efforts. In sum, we conclude that existing mechanisms aiming to explain the interaction between two adopting groups involved in the diffusion of innovation fails to adequately account for the diffusion pattern of co-dependent innovation.

Given the failure of replication, we resort to the robust Bass modelling approach and propose to model the interaction between the adopting groups with the churn rates in Chapter 3. The diffusion of service model with churn rate proposed in Libai et al. (2009) is adopted and applied to the co-dependent diffusion context with two distinct adopting groups. Results show the usefulness of churn rates as a proxy for interaction effects in the co-dependent diffusion, as their absence leads to the underestimation of growth potential and misrepresentation of innovation effects and imitation effects within each adopting group. Merchants exhibit a higher churn rate than consumers in the studied innovation diffusion, against the common wisdom that cost-bearers are more likely to churn given the impact on the bottom line. Simulation results show that as churn rates increase, there is a nonlinear increase in the imitation effect and a decrease in the innovation effect.

In Chapter 4, we take a further step to account for the dynamics between the adopting groups with a Vector Error Correction Model (VECM). Results of the co-integration test confirm a co-integrated relationship between the merchant usage and consumer usage, which can be translated into a long-run equilibrium between the adopting groups. The results of the VECM provide further understanding of the temporal pattern of the innovation diffusion on each side with a significant mean reverting factor. The Impulse Response Functions (IRF) associated with the VECM indicate that consumer response to a shock in the merchant usage is largest in the long-run while the merchant response to a shock in the consumer usage is largest in the short-run. Common wisdom suggests merchants are responsive to the adoption level on consumer side as merchants strive to meet the expectation of consumers and follow the trend that consumers follow. Our results refute this and point out that merchants are most responsive to changes on consumers' usage decision immediately after the change is observed. On the contrary, consumers exhibit gradual response to changes in merchants' usage, but the response is in fact more prominent and pro-longed.

Based on the findings from the three studies, we offer the following answers to the research questions addressed at the beginning of the thesis as follows.

<u>How does co-dependent innovation diffuse in a two-sided market and what modelling approach can be used to explain the co-dependent diffusion pattern?</u>

The co-dependent diffusion of innovation relies on the cooperative interaction between the two adopting groups. There is also likely to be a cointegrated relationship between the adopting group in the long run. That being said, the results shown in the third study reported in Chapter 4 demonstrate that any shock from one side of the market will not die down as those marketing mix effects normally would. Instead, the shock will boost the diffusion to the next level on the other side, and then contribute to the growth of the side that got the shock initially.

Given all the tests performed, we conclude that the VECM model is useful for explaining the interaction between the adoption groups and showing the dynamics between the adopting groups along the diffusion process.

<u>RQ1: What mechanism(s) underlying the interrelated or platform-based innovations can be used to explain the co-dependent diffusion of payment method innovation? Do existing models perform adequately in the context of co-dependent diffusion?</u>

The study presented in Chapter 2 answered RQ1 about whether the existing modelling mechanisms are found sufficient to describe the co-dependent diffusion pattern. The short answer is no. We fail to fully replicate any of the selected frameworks, although they are theoretically relevant. The replication of Bucklin and Sengupta (1993b) unveils the limitation of the multi-product growth model based on the Bass modelling framework in accommodating high correlations between the co-dependent innovations. The high correlation between the involved innovations is a signature of co-dependent innovations, as their functionality requires the simultaneous uptake of the other innovation. Symmetric feedback effects are found with the model proposed in Stremersch et al. (2007), while in the original study, the authors conclude that even one-way effects are not commonly observed, and thus the two-way effects are rare. Our results of two-ways effects echo the existence of co-dependency between the adopting groups that the replicated model fails to depict. Among the eight pairs of relationships tested in Hinz et al. (2020), our study with payment data only manages to replicate two out of eight. Results in Hinz et al. (2020) show competition effects within the same side of the market and enhancement effects across sides. The competition effects may raise from the limited resources provided on certain "competitive" markets, and thus may not be applicable to non-competitive markets where the general goal is to grow the innovation in the market. Our failure to fully replicate the selected studies demonstrates the importance of building a robust model that caters to the general diffusion pattern while specifying an appropriate term that represents the level of interaction between the adopting groups.

RQ2: Can the Bass model proposed for service innovation be used to depict the co-dependent service innovation? If yes, what can be used to explain the interaction between adopting groups?

The second study presented in Chapter 3 provides substantive evidence of how the payment method innovation data fits in the Bass model with churn rates. As the Bass model is usually applied to single innovation diffusion, we first confirm the diffusion path of contactless cards by consumers differs from that of contactless terminals by merchants, given the different magnitudes of innovation effect and imitation effect of each path. Merchants are found with strong imitation effect while the contactless card diffusion, based on consumer usage, is mostly driven by innovation effect. These results indicate that the diffusion of co-dependent innovation differs across the two adopting groups and there could be some mismatch between the two sides that drives or impedes the diffusion process. Therefore, we propose the churn rate, which is also find influential in other service innovation diffusion, as the proxy of the interaction outcomes between the two sides. Merchants are found with a higher average churn rate than consumers, and the churn rates of merchants varied with industries. Industries that gradually build up usage cases from the introduction stage of the innovation tend to witness less user churning, while the industries catching up during the growth stage tend to have higher churn rates.

RQ3: How does the co-dependency between the adopting groups impact the co-dependent diffusion over time?

The third study presented in Chapter 4 takes one step further to understand the dynamics between the adopting groups in the co-dependent diffusion of innovation. Johansen Cointegration Test results confirm the co-movement between the diffusion of contactless payment on the consumer side and that on the merchant side. Therefore, when there is a shock in either side of the market (i.e., within either adopting group), there is a corresponding movement in the other group that answers to the change across sides. In terms of how reliant each side is towards the variation of diffusion within the other side, we observe consumers are more sensitive in terms of the response magnitude and the level of significance than merchants. Consumers tend to shift their behaviour when they have unsatisfactory experience when using contactless payment innovation at the checkout, and this swift behavioural change is more prominent in the introduction stage and early growth stage of the diffusion, as evidenced by the rolling window analysis. As the co-dependent innovation diffuses with a larger user base, the co-dependency between the adopting groups gradually dies out. Another finding with the study lies in the long-term trend reflected in the impulse response functions. Unlike the transitory impact of marketing mix factors on sales or usage growth, the shock from one adopting group tends to have lasting impact on the other group, exhibiting a permanent change to the diffusion path of co-dependent innovations.

5.2 Theoretical Implications

The current work provides theoretical implications for co-dependent innovation. We distinguish co-dependent innovation from its close relatives, such as complementary, contingent, and hardware-software paradigm. Two aspects specify the difference between the co-dependent innovation from the rest: the requirement of uptake from two distinct adoption groups and the requirement of joint uptake simultaneously.

To examine whether the difference between the co-dependent innovations and existing innovation categories requires a new modelling framework to depict diffusion, we conducted differentiated replication and assessed the empirical generalizability of past studies (Uncles & Kwok, 2013). The replication results reveal the theoretical limitations of the models selected for replication. Specifically, the multi-product growth model under the Bass modelling framework fails to accommodate growth data with high correlation. The diffusion of complementary innovations such as scanner and UPC can have divergent paths due to factors such as pricing or cannibalization from the new generation. In contrast, the diffusion paths of co-dependent innovation, are likely to be highly correlated as a result of the co-dependency between the innovations and between the adopting groups. Therefore, the presence of high correlation between the diffusion of the involved innovation could represent a boundary condition for the model proposed in Bucklin and Sengupta (1993b).

The research of Stremersch et al. (2007), using an imbalanced model structure, concludes that indirect network effects in the hardware-software paradigm are rare. However, it may be the model specification and the data choice that result in the rareness of indirect network effects, as the present study showed different results. A balanced modelling structure could be more powerful in depicting the effects from two sides without subjective restriction on whether the cumulative sales (usage) or the incremental sales (usage) affect the growth of the related innovations.

Furthermore, our partial replication of the two-sided market model proposed in Hinz et al. (2020) demonstrates the limitation of the theoretical assumption that users on the same side demonstrate competition effects within each side while users across sides show enhancement to the other side. Fixing the number of lags at one period also limits the impact of existing users on the influxes and outflows of users to be sourced from the most recent period only.

In addition, we probed into the driving forces of the co-dependent diffusion of innovation and found the direct interaction effect between the adopting groups to be either proxied by the churn rates on each side of diffusion or examined directly with the system of equations modelling approach. The diffusion of co-dependent innovations is driven not only by the initial uptake as the result of advertising and word-of-mouth communication but also by the short-term usage fluctuation from both sides. It would stretch the idea of network effects in the co-dependent diffusion context to depict the interaction between both sides as network effects.

The present work also provides a detailed modelling framework that can be applied to study co-dependent innovations in other contexts, allowing the further accumulation of knowledge and testing of theoretical frameworks in this area of growing importance.

5.3 Managerial Implications

Results in the current thesis provide significant managerial implications for innovation providers in the diffusion process of co-dependent innovation. First, the findings on the churn rates inform innovation providers in two aspects. The average churn rates are differed between consumers and merchants, driving the efforts on user retention for innovation providers to be mainly focused on the merchant side. In addition, the churn rates, which we propose to represent the interaction between the adopting groups, varied by industries for merchants. Results further show that the churn rates are less associated with the industry type but more with the time when the industry started to adopt the innovation in general, providing insights for innovation enablers on the importance of attending to the late adopters. As churn rates are negatively correlated with the imitation effect, a higher churn rate in the late adopting industry can spell a spiralling impact on both the consumer and merchant sides, as the low imitation effect among merchants can discourage consumer usage via interactions.

The level of responsiveness as the output of VECM offers managerial implication on user acquisition by informing innovation providers about “whom to target first”. Given the evidence that consumers are more sensitive to the changes in the merchant usage outcome and consumers' response is the highest in the long run, innovation providers shall prioritize the promoting efforts on the merchant side to stir a short-term boost, which later translated into a long-run lift on the consumer side. Going hard and early, the merchant usage will generate the desired response on the consumer side, and this response can last beyond a short period (i.e., 6 weeks). Meanwhile, merchants who adopt early with a larger user base will experience less friction when the diffusion in the market in general picks up. Fewer hiccups in the usage decision on both sides of the market will help both adopting groups form payment method loyalty and sustain the diffusion of payment innovation.

5.4 Limitations and Future Directions

Although pioneering in examining the co-dependent diffusion of innovation and proposing the VECM framework to understand the co-dependency between the adopting group, the current work is not free of limitations.

One limitation lies in the data source. As with many other empirical studies relying on data from a single source of a single market, there is criticism regarding the data limitation and thus questioning the generalizability of the findings. Setting out to study co-dependent innovation, our empirical work relies solely on the payment method data set provided by a leading payment network operator in a developed western country. Therefore, there is no variation in the country-specific factors and no boundary testing about whether other co-dependent innovations can be adequately understood with the proposed method. We are aware that payment method innovation tends to rely heavily on the "usage case", as the prosperity of the innovation is determined by how many consumers and merchants use this innovation. Other co-dependent innovations, albeit the co-dependency embedded within the innovations and between the adopting groups, may also be impacted by the price of the innovations and the subscription or charge plans if they are service based. Then it will be interesting to know how much the variation of the diffusion outcome can still be attributed to the co-dependency and how much could be resulted from other marketing mix factors such as pricing.

Another limitation lies in the data measurement. As the daily usage measurement per card and terminal is impossible to track due to the enormous transaction volume daily, we adopt the count data to represent the usage. However, count data can only depict the binary outcome – "either being used or not being used" – of a card or a terminal during the studied time. We do not measure the "frequency" of usage. This limits our insight into how frequent users of co-dependent innovation impact the diffusion outcome. It could be the case that certain merchants in certain industries have more frequent users than sporadic users. However, this limitation could be attenuated if consumers form loyalty to their primed way of paying and will use a certain method for retailing purchases out of their habits. This has been proven by Wright (2002), and so far, no other work challenges this conclusion.

The third limitation lies in the utilisation of net change of users instead of the distinction between user influx and outflow. Although the modelling framework proposed in Hinz et al. (2020) is informative regarding tackling the user influx and outflow on both sides of the market, the VECM we proposed in Chapter 4 is based on the net change of users. Apart from the data availability limitation mentioned above, we also base our decision of model specification on reflecting the diffusion pattern of the innovation in general. Influx and outflow of users tend to be more appropriate when the studied population is a subset of the whole population. For payment method innovation, the impact of this limitation may be immaterial as the majority will utilise at least one payment method to pay. However, for other types of co-dependent innovation, applying user influx and outflow to the modelling framework could be appropriate.

We believe that our work can pave the way for future research in this important area. Future research can address the limitations listed above to help build a comprehensive understanding of the co-dependent diffusion of innovation.

Reference List

Accenture. (2017). Driving the future. In Accenture (Vol. 7, Issue 10). Downloaded from www.accenture.com/10PaymentsTrends on 10 July 2022

Adner, R., & Kapoor, R. (2016). Innovation ecosystems and the pace of substitution: Re-examining technology S-curves. Strategic Management Journal, 37(4), 625–648. https://doi.org/10.1002/smj.2363

Ailawadi, K. L., & Neslin, S. A. (1998). The Effect of Promotion on Consumption: Buying More and Consuming It Faster. Journal of Marketing Research, 35(3), 390. https://doi.org/10.2307/3152036

Ajzen, I. (1991). The Theory of Planned Behavior. Organizational Behavior and Human Decision Processes, 50(1), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alvarez, F., & Lippi, F. (2013). The demand of liquid assets with uncertain lumpy expenditures. Journal of Monetary Economics, 60(7), 753–770. https://doi.org/10.1016/j.jmoneco.2013.05.008

Antonides, G., Bas Amesz, H., & Hulscher, I. C. (1999). Adoption of payment systems in ten countries – a case study of diffusion of innovations. European Journal of Marketing, 33(11/12), 1123–1135. https://doi.org/10.1108/03090569910292302

Arango, C. A., Huynh, K. P., & Sabetti, L. (2015). Consumer payment choice: Merchant card acceptance versus pricing incentives. Journal of Banking and Finance, 55, 130–141. https://doi.org/10.1016/j.jbankfin.2015.02.005

Armstrong, M. (2006). Competition in two-sided markets. 37(3), 668–691.

Au, Y. A., & Kauffman, R. J. (2008). The economics of mobile payments: Understanding stakeholder issues for an emerging financial technology application. Electronic Commerce Research and Applications, 7(2), 141–164. https://doi.org/10.1016/j.elerap.2006.12.004

Bakshi, N., Hosanagar, K., & Bulte, C. Van Den. (2007). New Product Diffusion with Two Interacting Segments or Products (Issue 215). https://repository.upenn.edu/marketing_papers/375

Bass, F. M. (1969). A New Product Growth for Model Consumer Durables. Management Science, 15(5), 215–227. http://www.jstor.org/stable/2628128

Basu, A., Mazumdar, T., & Raj, S. P. (2003). Indirect network externality effects on product attributes. Marketing Science, 22(2), 209–221. https://doi.org/10.1287/mksc.22.2.209.16037

Bayus, B. L. (1987). Forecasting sales of new contingent products: An application to the compact disc market. The Journal of Product Innovation Management, 4(4), 243–255. https://doi.org/10.1016/0737-6782(87)90028-2

Bell, D. R., & Lattin, J. M. (1998). Shopping behavior and consumer preference for store price format: Why "large basket" shoppers prefer EDLP. Marketing Science, 17(1), 66–88. https://doi.org/10.1287/mksc.17.1.66

Binken, J. L. G., & Stremersch, S. (2009). The effect of superstar software on hardware sales in system markets. Journal of Marketing, 73(2), 88–104. https://doi.org/10.1509/jmkg.73.2.88

Block, J., & Kuckertz, A. (2018). Seven principles of effective replication studies: strengthening the evidence base of management research. Management Review Quarterly, 68(4), 355–359. https://doi.org/10.1007/s11301-018-0149-3

Bronnenberg, B. J., Mahajan, V., & Vanhonacker, W. R. (2000). The emergence of market structure in new repeat-purchase categories: The interplay of market share and retailer distribution. Journal of Marketing Research, 37(1), 16–31. https://doi.org/10.1509/jmkr.37.1.16.18723

Bucklin, L. P., & Sengupta, S. (1993a). Organizing Successful Co-Marketing Alliances. Journal of Marketing, 57(2), 32. https://doi.org/10.2307/1252025

Bucklin, L. P., & Sengupta, S. (1993b). The co-diffusion of complementary innovations: Supermarket scanners and UPC symbols. The Journal of Product Innovation Management, 10(2), 148–160. https://doi.org/10.1016/0737-6782(93)90006-C

Caillaud, B., & Jullien, B. (2003). Chicken & Egg : Competition among Intermediation Service Providers Published by : Wiley on behalf of RAND Corporation Chicken & egg : competition among intermediation service providers. RAND Journal of Economics, 34(2), 309–328.

Carbó-Valverde, S., Chakravorti, S., & Fernandez, F. R. (2016). The role of interchange fees in two-sided markets: An empirical investigation on payment cards. Review of Economics and Statistics, 98(2), 367–381.

Cenamor, J., Usero, B., & Fernández, Z. (2013). The role of complementary products on platform adoption: Evidence from the video console market. Technovation, 33(12), 405–416. https://doi.org/10.1016/j.technovation.2013.06.007

Chandran, C., Matthews, C., & Tripe, D. (2005). Competition in the New Zealand credit card market from the consumer perspective. Journal of Asia-Pacific Business, 6(1), 59–74. https://doi.org/10.1300/J098v06n01_04

Chandrasekaran, D., & Tellis, G. J. (2015). A Critical Review of Marketing Research on Diffusion of New Products. In Review of Marketing Research (pp. 39–80). https://doi.org/10.1108/S1548-6435(2013)10

Chandrasekaran, D., Tellis, G. J., & James, G. M. (2022). Leapfrogging, Cannibalization, and Survival During Disruptive Technological Change: The Critical Role of Rate of Disengagement. Journal of Marketing, 86(1), 149–166. https://doi.org/10.1177/0022242920967912

Chen, K. M., & Liu, R. J. (2005). Interface strategies in modular product innovation. Technovation, 25(7), 771–782. https://doi.org/10.1016/j.technovation.2004.01.013

Chen, Y., & Wang, L. (Tarry). (2019). Commentary: Marketing and the Sharing Economy: Digital Economy and Emerging Market Challenges. Journal of Marketing, 83(5), 28–31. https://doi.org/10.1177/0022242919868470

Ching, A. T., & Hayashi, F. (2010). Payment card rewards programs and consumer payment choice. Journal of Banking and Finance, 34(8), 1773–1787. https://doi.org/10.1016/j.jbankfin.2010.03.015

Clements, M. T., & Ohashi, H. (2005). Indirect network effects and the product cycle: Video games in the U.S., 1994-2002. Journal of Industrial Economics, 53(4), 515–542. https://doi.org/10.1111/j.1467-6451.2005.00268.x

Corritore, C. L., Kracher, B., & Wiedenbeck, S. (2003). On-line trust: Concepts, evolving themes, a model. International Journal of Human Computer Studies, 58(6), 737–758. https://doi.org/10.1016/S1071-5819(03)00041-7

Dahlberg, T., Guo, J., & Ondrus, J. (2015). A critical review of mobile payment research. Electronic Commerce Research and Applications, 14(5), 265–284. https://doi.org/10.1016/j.elerap.2015.07.006

Danaher, P. J. (2002). Optimal pricing of new subscription services: Analysis of a market experiment. Marketing Science, 21(2), 119–138. https://doi.org/10.1287/mksc.21.2.119.147

Datta, H., Foubert, B., & van Heerde, H. J. (2015). Are Free-Trial Customers Worth Less than Regular Customers? Journal of Marketing Research, LII(April), 217–234. https://doi.org/10.2139/ssrn.2060645

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly: Management Information Systems, 13(3), 319–339. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., Warshaw, P. R., & Paul R. Warshaw. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Mode. Management Science, 35(8), 982–1003. https://doi.org/10.1007/sl0734-011-9486-z

De Best, R. (2019). Payment Methods in Europe - Statistics & Facts. Www.Statista.Com. https://www.statista.com/topics/3946/digital-payment-methods-in-europe/

De Kerviler, G., Demoulin, N. T. M., & Zidda, P. (2016a). Adoption of in-store mobile payment: Are perceived risk and convenience the only drivers? Journal of Retailing and Consumer Services, 31, 334–344. https://doi.org/10.1016/j.jretconser.2016.04.011

De Kerviler, G., Demoulin, N. T. M., & Zidda, P. (2016b). Adoption of in-store mobile payment: Are perceived risk and convenience the only drivers? Journal of Retailing and Consumer Services, 31, 334–344. https://doi.org/10.1016/j.jretconser.2016.04.011

De Luna, I. R., Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2018). Mobile payment is not all the same: The adoption of mobile payment systems depending on the technology applied. Technological Forecasting and Social Change, October 2017, 1–14. https://doi.org/10.1016/j.techfore.2018.09.018

Dekimpe, M. G., & Hanssens, D. M. (1996). Sustained spending and persistent response: A new look at long-term marketing profitability. Journal of Marketing Research, 36(4), 397-412.

Dekimpe, M. G., Parker, P. M., & Sarvary, M. (2000). Global diffusion of technological innovations: A coupled-hazard approach. Journal of Marketing Research, 37(1), 47–59. https://doi.org/10.1509/jmkr.37.1.47.18722

Dewan, S. G., & Chen, L. (2005). Mobile Payment Adoption in the US: A Cross-industry, Cross-platform Solution. Journal of Information Privacy & Security, 1(2), 4–28. https://doi.org/10.1080/15536548.2005.10855765

Dewan, S., Ganley, D., & Kraemer, K. L. (2010). Complementarities in the diffusion of personal computers and the internet: Implications for the global digital divide. Information Systems Research, 21(4), 925–940. https://doi.org/10.1287/isre.1080.0219

Dickey, D., & Fuller, W. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. Econometrica, 49(4), 1057–1072. http://www.jstor.org/stable/1912517

Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for two-sided markets. Harvard Business Review, 84(10). https://doi.org/10.1007/s00199-006-0114-6

Evans, D. S. (2003). Some Empirical Aspects of Multi-sided Platform Industries. SSRN Electronic Journal, 2(3), 191–209. https://doi.org/10.2139/ssrn.447981

Evans, D. S. (2009). Some Empirical Aspects of Multi-sided Platform Industries. Review of Network Economics, 2(3), 191–209. https://doi.org/10.2202/1446-9022.1026

Evans, D. S., & Schmalensee, R. (2005). The Industrial Organization of Markets With Two-Sided Platforms. In NBER Working Paper No. 11603 (Issue September).

Falk, T., Kunz, W. H., Schepers, J. J. L., & Mrozek, A. J. (2016). How mobile payment influences the overall store price image. Journal of Business Research, 69(7), 2417–2423. https://doi.org/10.1016/j.jbusres.2016.01.011

Fang, E., Li, X., Huang, M., & Palmatier, R. W. (2015). Direct and indirect effects of buyers and sellers on search advertising revenues in business-to-business electronic platforms. Journal of Marketing Research, 52(3), 407–422. https://doi.org/10.1509/jmr.13.0165

Feinberg, R. A. (1986). Credit Cards as Spending Facilitating Stimuli : A Conditioning Interpretation. Journal of Consumer Research, 13(3), 348–356. https://doi.org/10.1086/209074

Fok, D., Horváth, C., Paap, R., & Franses, P. H. (2006). A hierarchical bayes error correction model to explain dynamic effects of price changes. Journal of Marketing Research, 43(3), 443–461. https://doi.org/10.1509/jmkr.43.3.443

Foubert, B., & Gijsbrechts, E. (2016). Try it, you'll like it—or will you? The perils of early free-trial promotions for high-tech service adoption. Marketing Science, 35(5), 810–826. https://doi.org/10.1287/mksc.2015.0973

Franses, P. H. (1994). A multivariate approach to modeling univariate seasonal time series. Journal of Econometrics, 63(1), 133-151.

Gagliardi, D., Ramlogan, R., Navarra, P., & Dello Russo, C. (2018). Diffusion of complementary evolving pharmaceutical innovations: The case of Abacavir and its pharmacogenetic companion diagnostic in Italy. Technological Forecasting and Social Change, 134(April), 223–233. https://doi.org/10.1016/j.techfore.2018.06.014

Gjika, E., Basha, L., Puka, L., & Shahini, I. (2019). ATMS and POS diffusion: An econometric model Albania case study. ACM International Conference Proceeding Series, 59–63. https://doi.org/10.1145/3328886.3328899

Goldenberg, J., Libai, B., & Muller, E. (2002). Riding the saddle: How cross-market communications can create a major slump in sales. Journal of Marketing, 66(2), 1–16. https://doi.org/10.1509/jmkg.66.2.1.18472

Goldenberg, J., Libai, B., & Muller, E. (2010). The chilling effects of network externalities. International Journal of Research in Marketing, 27(1), 4–15. https://doi.org/10.1016/j.ijresmar.2009.06.006

Greenacre, L., & Akbar, S. (2019). The impact of payment method on shopping behaviour among low income consumers. Journal of Retailing and Consumer Services, 47

(October 2018), 87–93. https://doi.org/10.1016/j.jretconser.2018.11.004

Greenhalgh, T., Robert, G., Macfarlane, F., & Bate, P. (2004). Diffusion of Innovations in Service Organizations : Systematic Review and Recommendations. Milbank Quarterly, 82(4), 581–629.

Gretz, R. T., Malshe, A., Bauer, C., & Basuroy, S. (2019). The impact of superstar and non-superstar software on hardware sales: the moderating role of hardware lifecycle. Journal of the Academy of Marketing Science, 47(3), 394–416. https://doi.org/10.1007/s11747-019-00631-3

Gruber, M. (2020). An evolutionary perspective on adoption-diffusion theory. Journal of Business Research, 116 (March), 535–541. https://doi.org/10.1016/j.jbusres.2020.02.024

Gupta, S., Jain, D. C., & Sawhney, M. S. (1999). Modeling the evolution of markets with indirect network externalities: An application to digital television. Marketing Science 18(3), 396–416. https://doi.org/10.1287/mksc.18.3.396

Hafalir, E. I., & Loewenstein, G. F. (2011). The Impact of Credit Cards on Spending: A Field Experiment. SSRN Electronic Journal, April 2009. https://doi.org/10.2139/ssrn.1378502

Hamilton, J. D. (1994). Time Series Analysis. In Princeton University Press.

Hinz, O., Otter, T., & Skiera, B. (2020). Estimating Network Effects in Two-Sided Markets. Journal of Management Information Systems, 37(1), 12–38. https://doi.org/10.1080/07421222.2019.1705509

Hirschman, E. C. (1979). Differences in Consumer Purchase Behavior by Credit Card Payment System. Journal of Consumer Research, 6(1), 58. https://doi.org/10.1086/208748

Hogan, J. E., Lemon, K. N., & Libai, B. (2003). What Is the True Value of a Lost Customer? Journal of Service Research, 5(3), 196–208. https://doi.org/10.1177/1094670502238915

Hubbard, R., Vetter, D. E., & Little, E. L. (1998). Replication in Strategic Management: Scientific Testing for Validity, Generalizability, and Usefulness. Strategic management journal, 19(3), 243-254. https://www.jstor.org/stable/3094098

Humbani, M., & Wiese, M. (2019). An integrated framework for the adoption and continuance intention to use mobile payment apps. International Journal of Bank Marketing. https://doi.org/10.1108/IJBM-03-2018-0072

Hussain, M., Mollik, A. T., Johns, R., & Rahman, M. S. (2019). M-payment adoption for bottom of pyramid segment: an empirical investigation. International Journal of Bank Marketing, 37(1), 362–381. https://doi.org/10.1108/IJBM-01-2018-0013

Iyengar, R., Bulte, C. Van Den, & Choi, J. (2011). Distinguishing among Mechanisms of

Social Contagion in New Product Adoption : Framework and Illustration. MSI Working Paper, Report No. 11-119.

Johansen, S. (1988). Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12(2–3), 231–254. https://doi.org/10.1016/0165-1889(88)90041-3

Johnson, V. L., Kiser, A., Washington, R., & Torres, R. (2018). Limitations to the rapid adoption of M-payment services: Understanding the impact of privacy risk on M-Payment services. Computers in Human Behavior, 79, 111–122. https://doi.org/10.1016/j.chb.2017.10.035

Jonker, N. (2019). What drives the adoption of crypto-payments by online retailers? Electronic Commerce Research and Applications, 35(April), 100848. https://doi.org/10.1016/j.elerap.2019.100848

Juselius, K. (2006). The Cointegrated VAR model. Methdology and Application. Advanced Texts in Econometrics. Oxford Universtiy Press.

Kalinic, Z., Marinkovic, V., Molinillo, S., & Liébana-Cabanillas, F. (2019). A multi-analytical approach to peer-to-peer mobile payment acceptance prediction. Journal of Retailing and Consumer Services, 49(December 2018), 143–153. https://doi.org/10.1016/j.jretconser.2019.03.016

Katz, M. L., & Shapiro, C. (1985a). Network Externalities, Competition, and Compatibility. American Economic Review, 75(3), 424–440.

Katz, M. L., & Shapiro, C. (1985b). Network Externalities , Competition , and Compatibility. The American Economic Review, 75(3), 424–440.

Katz, M. L., & Shapiro, C. (1986). Technology Adoption in the Presence of Network Externalities. Journal of Political Economy, 94(4), 822–841. https://www.jstor.org/stable/1833204

Katz, M. L., & Shapiro, C. (1994). Systems Competition and Network Effects. Journal of Economic Perspectives, 8(2), 93–115. https://doi.org/10.1257/jep.8.2.93

Kerr, G., Schultz, D. E., & Lings, I. (2016). “Someone Should Do Something”: Replication and an agenda for collective action. Journal of Advertising, 45(1), 4–12. https://doi.org/10.1080/00913367.2015.1077492

Khalilzadeh, J., Ozturk, A. B., & Bilgihan, A. (2017). Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry. Computers in Human Behavior, 70(2017), 460–474. https://doi.org/10.1016/j.chb.2017.01.001

Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. Computers in Human Behavior, 26(3), 310–322. https://doi.org/10.1016/j.chb.2009.10.013

Kim, S. S., & Malhotra, N. K. (2005). Predicting system usage from intention and past use: Scale issues in the predictors. Decision Sciences, 36(1), 187–196. https://doi.org/10.1111/j.1540-5915.2005.00070.x

Knittel, C. R., & Stango, V. (2004). Incompatibility and Consumer Demand: Evidence from ATMs. NBER Working Paper Series, W-10962

Koenig-Lewis, N., Marquet, M., Palmer, A., & Zhao, A. L. (2015). Enjoyment and social influence: predicting mobile payment adoption. Service Industries Journal, 35(10), 537–554. https://doi.org/10.1080/02642069.2015.1043278

Kumar, V., Nim, N., & Sharma, A. (2019). Driving growth of Mwallets in emerging markets: a retailer's perspective. Journal of the Academy of Marketing Science, 47(4), 747–769. https://doi.org/10.1007/s11747-018-0613-6

Kumar, V., & Reinartz, W. (2012). Customer Relationship Management. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-20110-3

Kumar, V., & Reinartz, W. (2016). Creating Enduring Customer Value. Journal of Marketing, 80(6), 36–68. https://doi.org/10.1509/jm.15.0414

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of Econometrics, 54(1–3), 159–178. https://doi.org/10.1016/0304-4076(92)90104-Y

Ladrón de Guevara, A., Elberse, A., & Putsis, W. P. (2007). Diffusion of Complementary Products with Network Effects : A Model and Application (Issue May).

Landsman, V., & Stremersch, S. (2011). Multihoming in Two-Sided Markets : An Empirical Inquiry in the Video. Journal of Marketing, 75(November), 39–54. https://doi.org/10.1509/jm.09.0199

Laukkanen, T. (2016). Consumer adoption versus rejection decisions in seemingly similar service innovations: The case of the Internet and mobile banking. Journal of Business Research, 69(7), 2432–2439. https://doi.org/10.1016/j.jbusres.2016.01.013

Lee, H., Kim, S. G., Park, H. woo, & Kang, P. (2014). Pre-launch new product demand forecasting using the Bass model: A statistical and machine learning-based approach. Technological Forecasting and Social Change, 86, 49–64. https://doi.org/10.1016/j.techfore.2013.08.020

Lee, J., Ryu, M. H., & Lee, D. (2019). A study on the reciprocal relationship between user perception and retailer perception on platform-based mobile payment service. Journal of

Retailing and Consumer Services, 48(January), 7–15. https://doi.org/10.1016/j.jretconser.2019.01.007

Leonard-Barton, D. (1981). Voluntary Simplicity Lifestyles and Energy Conservation. Journal of Consumer Research, 8(3), 243. https://doi.org/10.1086/208861

Leong, L. Y., Hew, T. S., Tan, G. W. H., & Ooi, K. B. (2013). Predicting the determinants of the NFC-enabled mobile credit card acceptance: A neural networks approach. Expert Systems with Applications, 40(14), 5604–5620. https://doi.org/10.1016/j.eswa.2013.04.018

Libai, B., Muller, E., & Peres, R. (2009). The diffusion of services. Journal of Marketing Research, 46(2), 163–175. https://doi.org/10.1509/jmkr.46.2.163

Liébana-Cabanillas, F., Molinillo, S., & Ruiz-Montañez, M. (2019). To use or not to use, that is the question: Analysis of the determining factors for using NFC mobile payment systems in public transportation. Technological Forecasting and Social Change, 139(November 2018), 266–276. https://doi.org/10.1016/j.techfore.2018.11.012

Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2014). Antecedents of the adoption of the new mobile payment systems: The moderating effect of age. Computers in Human Behavior, 35, 464–478. https://doi.org/10.1016/j.chb.2014.03.022

Lilien, G. L., Rangaswamy, A., & Bulte, C. Van Den. (2000). Diffusion Models : Managerial Applications and Software. New-Product Diffusion Models, 3004(814), 295–332.

Liu, Y., & Dewitte, S. (2021). A replication study of the credit card effect on spending behavior and an extension to mobile payments. Journal of Retailing and Consumer Services, 60(January), 102472. https://doi.org/10.1016/j.jretconser.2021.102472

Lütkepohl, H. (2005). New introduction to multiple time series analysis. In New introduction to Multiple Time Series Analysis. https://doi.org/10.1007/978-3-540-27752-1

Mahajan, V., & Muller, E. (1979). Innovation Diffusion and New Product Growth Models in Marketing. Journal of Marketing, 43(4), 55. https://doi.org/10.2307/1250271

Mahajan, V., & Peterson, R. A. (1978). Innovation Diffusion in a Dynamic Potential Adopter Population. Management Science, 24(15), 1589–1597.

Mahajan, V., Peterson, R. A., Jain, A. K., & Malhotra, N. (1979). A new product growth model with a dynamic market potential. Long Range Planning, 12(4), 51–58. https://doi.org/10.1016/0024-6301(79)90120-1

Mallat, N. (2007). Exploring consumer adoption of mobile payments - A qualitative study. Journal of Strategic Information Systems, 16(4), 413–432. https://doi.org/10.1016/j.jsis.2007.08.001

Mantena, R., Sankaranarayanan, R., & Viswanathan, S. (2010). Platform-based information goods: The economics of exclusivity. Decision Support Systems, 50(1), 79–92. https://doi.org/10.1016/j.dss.2010.07.004

Markus, M. L., & Ortiz de Guinea, A. (2009). Why Break the Habit of a Lifetime? Rethinking the Roles of Intention, Habit, and Emotion in Continuing Information Technology Use. MIS Quarterly, 33(3), 433–444.

Martikainen, E., Schmiedel, H., & Takalo, T. (2015). Convergence of European retail payments. Journal of Banking and Finance, 50, 81–91. https://doi.org/10.1016/j.jbankfin.2014.09.021

McIntyre, D. P., & Srinivasan, A. (2017). Networks, platforms, and strategy: Emerging views and next steps. Strategic Management Journal, 38(1), 141–160. https://doi.org/10.1002/smj.2596

Meyer, P. E., & Winebrake, J. J. (2009). Modeling technology diffusion of complementary goods : The case of hydrogen vehicles and refueling infrastructure. Technovation, 29, 77–91. https://doi.org/10.1016/j.technovation.2008.05.004

Mezini, E., & Spaho, A. B. (2018). Modeling and forecasting the diffusion of ATM/POS terminals and debit/credit cards in Albania. CEUR Workshop Proceedings, 2280, 107–113.

Mueller-Langer, F., Fecher, B., Harhoff, D., & Wagner, G. G. (2019). Replication studies in economics—How many and which papers are chosen for replication, and why? Research Policy, 48(1), 62–83. https://doi.org/10.1016/j.respol.2018.07.019

Muzellec, L., Ronteau, S., & Lambkin, M. (2015). Two-sided Internet platforms: A business model lifecycle perspective. Industrial Marketing Management, 45(1), 139–150. https://doi.org/10.1016/j.indmarman.2015.02.012

Nair, H., Chintagunta, P. K., & Dube, J.-P. H. (2004). Empirical Analysis of Indirect Network Effects in the Market for Personal Digital Assistants. Quantitative Marketing and Economics, 2, 23–58. https://doi.org/10.2139/ssrn.408280

Niculescu, M. F., Shin, H., & Whang, S. (2012). Underlying consumer heterogeneity in markets for subscription-based IT services with network effects. Information Systems Research, 23(4), 1322–1341. https://doi.org/10.1287/isre.1120.0422

Niculescu, M. F., & Whang, S. (2012). Codiffusion of wireless voice and data services: An empirical analysis of the japanese mobile telecommunications market. Information Systems Research, 23(1), 260–279. https://doi.org/10.1287/isre.1100.0346

Norton, J. A., & Bass, F. M. (1987). A Diffusion Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products. Management Science, 33(9), 1069–1086. https://doi.org/10.1287/mnsc.33.9.1069

OECD. (2022). Gross domestic spending on R&D. https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm#indicator-chart

Oliveira, T. and Martins, M. F. (2011). Literature review of information technology adoption models at firm level. Electronic journal of information systems evaluation, 14(1), pp110-121. https://doi.org/10.1017/CBO9781107415324.004

Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. Computers in Human Behavior, 61(2016), 404–414. https://doi.org/10.1016/j.chb.2016.03.030

Ondrus, J., & Pigneur, Y. (2006). Towards a holistic analysis of mobile payments: A multiple perspectives approach. Electronic Commerce Research and Applications, 5(3), 246–257. https://doi.org/10.1016/j.elerap.2005.09.003

Pauwels, K., & Hanssens, D. M. (2007). Performance regimes and marketing policy shifts. Marketing Science, 26(3), 293–311. https://doi.org/10.1287/mksc.1060.0267

Peres, R., Muller, E., & Mahajan, V. (2010). Innovation diffusion and new product growth models: A critical review and research directions. International Journal of Research in Marketing, 27(2), 91–106. https://doi.org/10.1016/j.ijresmar.2009.12.012

Peterson, R. A., & Mahajan, V. (1978). Multi-product growth models. In J. N. Sheth (Ed.), Research in Marketing, Volume 1 (pp. 201–231). JAI PRESS INC.

Plouffe, C. R., Hulland, J. S., & Vandenbosch, M. (2001). Research Report: Richness Versus Parsimony in Modeling Technology Adoption Decisions—Understanding Merchant Adoption of a Smart Card-Based Payment System. Information Systems Research, 12(2), 208–222.

Plouffe, C. R., Vandenbosch, M., & Hulland, J. (2001). Intermediating technologies and multi-group adoption: A comparison of consumer and merchant adoption intentions toward a new electronic payment system. Journal of Product Innovation Management, 18(2), 65–81. https://doi.org/10.1111/1540-5885.1820065

Prelec, D., & Loewenstein, G. (1998). The Red and the Black: Mental Accounting of Savings and Debt. Marketing Science, 17(1), 4–28. https://doi.org/10.1037//1082-989X.5.2

Prelec, D., & Simester, D. (2001). Always Leave Home without It : A Further Investigation of the Credit-Card Effect on Willingness to Pay. Marketing Letters, 12(1), 5–12.

Putsis, W. P., Balasubramanian, S., Kaplan, E. H., & Sen, S. K. (1997). Mixing behavior in cross-country diffusion. Marketing Science, 16(4), 354–369. https://doi.org/10.1287/mksc.16.4.354

PwC. (2021). Navigating the payments matrix: Charting a course amid evolution and revolution. 1–30. Downloaded from https://www.pwc.com/gx/en/industries/financial-services/publications/financial-services-in-2025/payments-in-2025.html on 4 June 2022.

Qi, M., & Yang, S. (2003). Forecasting consumer credit card adoption: What can we learn about the utility function? International Journal of Forecasting, 19(1), 71–85. https://doi.org/10.1016/S0169-2070(01)00118-2

Raghubir, P., & Srivastava, J. (2008). Monopoly Money: The Effect of Payment Coupling and Form on Spending Behavior. Journal of Experimental Psychology: Applied, 14(3), 213–225. https://doi.org/10.1037/1076-898X.14.3.213

Raghubir, P., & Srivastava, J. (2009). The Denomination Effect. Journal of Consumer Research, 36(4), 701–713. https://doi.org/10.1086/599222

Ram, S., & Jung, H. S. (1991). “Forced” adoption of innovations in organizations: Consequences and implications. The Journal of Product Innovation Management, 8(2), 117–126. https://doi.org/10.1016/0737-6782(91)90005-J

Rochet, J.-C., & Tirole, J. (2002). Cooperation among Competitors : Some Economics of Payment Card Associations. The RAND Journal of Economics, 33(4), 549–570.

Rochet, J.-C., & Tirole, J. (2003). Platform Competition in Two-sided Markets. Journal of the European Economic Association, 1(4), 990–1029.

Rochet, J., & Tirole, J. (2006). Two-sided markets : a progress report. 37(3), 645–667.

Rogers, E. M. (1983). Diffusion of Innovations (3rd ed.).

Rogers, E. M. (2003). Diffusion of Innovations (5th ed.). Free Press.

Ronayne, D. (2011). Which Impulse Response Function? Warwick Economic Research Papers, 971, 1–46. http://www2.warwick.ac.uk/fac/soc/economics/staff/phd_students/dronayne.

Runnemark, E., Hedman, J., & Xiao, X. (2015). Do consumers pay more using debit cards than cash? Electronic Commerce Research and Applications, 14(5), 285–291. https://doi.org/10.1016/j.elerap.2015.03.002

Rysman, M. (2004). Networks : Competition Between A Study of the Market for Yellow Pages. Review of Economic Studies, 71(2), 483–512.

Rysman, M. (2007). An Empirical Analysis of Payment Card Usage. Journal of Industrial Economics, 55(1), 1–36. https://doi.org/10.1111/j.1467-6451.2007.00301.x

Said, S. E., & Dickey, D. A. (1984). Testing for Unit Roots in Autoregressive-Moving

Average Models of Unknown Order. Biometrika, 71(3), 599. https://doi.org/10.2307/2336570

Seamans, R., & Zhu, F. (2014). Responses to entry in multi-sided markets: The impact of craigslist on local newspapers. Management Science, 60(2), 476–493. https://doi.org/10.1287/mnsc.2013.1785

Shah, A. M., Eisenkraft, N., Bettman, J. R., & Chartrand, T. L. (2016). “Paper or plastic?”: How we pay influences post-transaction connection. Journal of Consumer Research, 42(5), 688–708. https://doi.org/10.1093/jcr/ucv056

Shao, Z., Zhang, L., Li, X., & Guo, Y. (2019). Antecedents of trust and continuance intention in mobile payment platforms: The moderating effect of gender. Electronic Commerce Research and Applications, 33(August 2018), 100823. https://doi.org/10.1016/j.elerap.2018.100823

Sharma, S. K., Mangla, S. K., Luthra, S., & Al-Salti, Z. (2018). Mobile wallet inhibitors: Developing a comprehensive theory using an integrated model. Journal of Retailing and Consumer Services, 45(June), 52–63. https://doi.org/10.1016/j.jretconser.2018.08.008

Shih, C. F., & Venkatesh, A. (2004). Beyond Adoption: Development and Application of a Use-Diffusion Model. Journal of Marketing, 68(1), 59–72. https://doi.org/10.1509/jmkg.68.1.59.24029

Shimp, T. A., & Moody, M. P. (2000). In search of a theoretical explanation for the credit card effect. Journal of Business Research, 48(1), 17–23. https://doi.org/10.1016/S0148-2963(98)00071-X

Shin, D. H. (2009). Towards an understanding of the consumer acceptance of mobile wallet. Computers in Human Behavior, 25(6), 1343–1354. https://doi.org/10.1016/j.chb.2009.06.001

Shu, W., & Cheng, C. Y. (2012). How to improve consumer attitudes toward using credit cards online: An experimental study. Electronic Commerce Research and Applications, 11(4), 335–345. https://doi.org/10.1016/j.elerap.2012.01.003

Siemens, J. C. (2007). When Consumption Benefits Precede Costs: Towards an Understanding of ‘Buy Now, Pay Later’ Transactions. Journal of Behavioral Decision Making, 20, 521–531. https://doi.org/10.1002/bdm

Singh, N., & Sinha, N. (2020). How perceived trust mediates merchant’s intention to use a mobile wallet technology. Journal of Retailing and Consumer Services, 52(March 2019), 101894. https://doi.org/10.1016/j.jretconser.2019.101894

Slade, E., Williams, M., Dwivedi, Y., & Piercy, N. (2015). Exploring consumer adoption of proximity mobile payments. Journal of Strategic Marketing, 23(3), 209–223. https://doi.org/10.1080/0965254X.2014.914075

Soman, D. (2001). Effects of Payment Mechanism on Spending Behavior: The Role of Rehearsal and Immediacy of Payments. Journal of Consumer Research, 27(4), 460–474. https://doi.org/10.1086/319621

Soman, D. (2003). The Effect of Payment Transparency on Consumption: Quasi-Experiments from the Field. Marketing Letters, 14(3), 173–183. https://doi.org/10.1023/A:1027444717586

Soman, D., & Cheema, A. (2002). The effect of credit on spending decisions: The role of the credit limit and credibility. Marketing Science, 21(1), 32–53. https://doi.org/10.1287/mksc.21.1.32.155

Stavins, J. (2018). Consumer preferences for payment methods: Role of discounts and surcharges. Journal of Banking and Finance, 94, 35–53. https://doi.org/10.1016/j.jbankfin.2018.06.013

Stremersch, S., Tellis, G. J., Franses, P. H., & Binken, J. L. G. (2007). Indirect network effects in new product growth. Journal of Marketing, 71(3), 52–74. https://doi.org/10.1509/jmkg.71.3.52

Tencent, RDCY, & Ipsos. (2017). 2017 Mobile payment usage in China report. August, 1–29. https://www.ipsos.com/sites/default/files/ct/publication/documents/2017-08/Mobile_payments_in_China-2017.pdf

Thomas, M., Desai, K. K., & Seenivasan, S. (2011). How Credit Card Payments Increase Unhealthy Food Purchases: Visceral Regulation of Vices. Journal of Consumer Research, 38(1), 126–139. https://doi.org/10.1086/657331

Uncles, M. D., & Kwok, S. (2013). Designing research with in-built differentiated replication. Journal of Business Research, 66(9), 1398–1405. https://doi.org/10.1016/j.jbusres.2012.05.005

V., K., & Reinartz, W. J. (n.d.). Customer Relationship Management.

Van Den Bulte, C. (2000). New product diffusion acceleration: Measurement and analysis. Marketing Science, 19(4), 366–380. https://doi.org/10.1287/mksc.19.4.366.11795

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425–478.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theoryof Acceptance and Use of Technology. MIS Quarterly, 36(1), 157–178.

Wang, Y. M., & Lin, W. (2019). Understanding Consumer Intention to Pay by Contacltess credit cards in Taiwan. International Journal of Mobile Communications, 17(1), 1–23.

Weyl, E. G. (2010). A Price Theory of Multi-Sided Platforms. The American Economic Review, 100(4), 1642–1672.

Wilbur, K. C. (2008). A Two-Sided, Empirical Model of Television Advertising and Viewing Markets. Marketing Science, 27(3), 356–378. https://doi.org/10.1287/mksc.1070.0303

WIPO. (2021). Global Innovation Index 2021: Tracking Innovation through the COVID-19 Crisis. In World Intellectual Property Organization (Issue 14th Edition). https://www.bloomberg.com/topics/global-innovation-index%0Ahttp://www.wipo.int/publications/ru/series/index.jsp?id=129

Wolfe, R. A. (1994). Organizational Innovation: Review, Critique and Suggested Research Direction. Journal of Management Studies, 31(3), 405-431.

Wooldridge, J. M. (2019). Introductory Econometrics: A Modern Approach (7th ed.).

Wright, M. (2002). Patterns of purchase loyalty for retail payment methods. International Journal of Bank Marketing, 20(7), 311–316. https://doi.org/10.1108/02652320210451205

Wright, M., Upritchard, C., & Lewis, T. (1997). A validation of the Bass new product diffusion model in New Zealand. Marketing Bulletin-Department of Marketing Massey University, 8(1961), 15–29.

Wu, F. S., & Chu, W. L. (2010). Diffusion models of mobile telephony. Journal of Business Research, 63(5), 497–501. https://doi.org/10.1016/j.jbusres.2009.04.008

Yao, M., Di, H., Zheng, X., & Xu, X. (2018). Impact of payment technology innovations on the traditional financial industry: A focus on China. Technological Forecasting and Social Change, 135(December 2017), 199–207. https://doi.org/10.1016/j.techfore.2017.12.023

Yli-Renko, H., & Janakiraman, R. (2008). How customer portfolio affects new product development in technology-based entrepreneurial firms. Journal of Marketing, 72(5), 131–148. https://doi.org/10.1509/jmkg.72.5.131

Zellermayer, O. (1997). The Pain of Paying.

Zervas, G., Proserpio, D., & Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of airbnb on the hotel industry. Journal of Marketing Research, 54(5), 687–705. https://doi.org/10.1509/jmr.15.0204

Zhang, C., Schmöcker, J. D., Kuwahara, M., Nakamura, T., & Uno, N. (2020). A diffusion model for estimating adoption patterns of a one-way carsharing system in its initial years. Transportation Research Part A: Policy and Practice, 136, 135–150. https://doi.org/10.1016/j.tra.2020.03.027

Zhang Foutz, N., & Rao, V. (2018). The state of new product design and forecasting research: recent developments and future directions. In P. N. Golder & D. Mitra (Eds.), Handbook of Research on New Product Development (pp. 173–206). Edward Elgar Publishing.

Zhu, F., & Iansiti, M. (2012). Entry Into Platform-Based Markets. Strategic Management Journal, 33(1), 88–106. https://doi.org/10.1002/smj.941

Zhu, F., & Zhang, X. (2010). Impact of Online Consumer Reviews on Sales : The Moderating Role of Product and Consumer. Journal of Marketing, 74(March), 133–148. https://doi.org/10.1509/jm.74.2.133