BNPLs vs Traditional Lenders:
Can innovative fintechs take over the credit card sector?

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Thesis submitted in fulfilment of the requirements for
the degree of Bachelor of Business (Honours)

Bachelor of Business (Honours)

2021

University of Technology Sydney

Faculty of Finance

22nd November 2021

Certificate of Original Authorship

I certify that the work in this thesis has not previously been submitted for a degree, nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text. I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signature of Student: Alizeh Zaidi

Date: 22 November 2021

Acknowledgements

I would like to thank the following people without whom this thesis may not have been possible:

Thomas Matthys for his consistent encouragement, support and suggestions for writing about a topic with not many prior studies;

Harry Scheule for his recommendations, wise words and experience, which allowed me to expand on various facets of research;

Honours Coordinator Vital Alexeev for his willingness to firstly answer all questions to the best of his ability and secondly, always make time for each student;

My industry mentor, Commonwealth Bank of Australia's CFO of Business Banking, Victoria Hickey, as her unending encouragement and insight enabled me to keep my end goal in mind even when it seemed I had reached a roadblock.

Thank you all for helping me along this year. I could not have asked for a better banking supervisory panel, honours coordinator or industry mentor.

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Abstract

The current retail climate has been riddled with financial uncertainty. In a bid to offer consumers a new financing solution, the rapidly growing buy now, pay later (BNPL) industry has disrupted the Australian market, transacting around $10 billion worth of purchases in 2020[1]. In this paper, I explore the popularity of this innovation, explicitly determining the effect of BNPL financial technology (fintech) operations on credit card lending in Australia. This research builds a foundation for future investigations into policy frameworks and the consumer concerns surrounding BNPLs. I find that BNPL operations have a consistently negative effect on credit card lending in the broader scope of the Australian market and, more specifically, on banks. The COVID pandemic has played a critical part in this effect as restrictive lockdown measures significantly offset online shopping.

Keywords: BNPL, Banks, fintechs, credit card, debit card

JEL Classification: G21, G23, G51

[1] (Fisher et al. 2021)

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1. Introduction

In a thriving retail sector, the growth of intensely popular BNPL services has disrupted the market, transacting around $10 billion worth of purchases in Australia and New Zealand alone in the 2020 financial year (Fisher et al. 2021). According to statistics collated by the Reserve Bank of Australia (RBA), credit cards in circulation dropped by 1 million in the same year and the amount owing by almost $8 billion. The following year, when the Commonwealth Bank of Australia (CBA) announced their new BNPL platform would launch in mid-2021, it was clear that banks were facing an intervention, and the metaphorical gauntlet had been thrown.

Within the past few decades, financial deregulation has increased competition and access to credit, ultimately allowing consumers the ability to choose a wide array of financing and investment vehicles (Consumer and Financial Literacy Taskforce 2004). Angus Sullivan, a CBA group executive, emphasised that *"customer needs are evolving, and this new BNPL offering is about giving customers more choice"* (CBA 2021)[2]. Therefore, it is clear that the impact of BNPL technology is vast, encouraging prominent market players to follow in the footsteps of companies like Afterpay and Zippay, climbing the ladder of disruptive innovation.

The technological advances of the 21st century are accompanied by individuals' desire for easy accessibility, especially for millennial[3] and Generation Z[4] consumers (Ridley 2019). This is where BNPL fintechs have asserted their claim over traditional credit card lenders. The rapid growth in popularity of BNPL platforms showcases positive consumer perception regarding the convenience and cost-effectiveness of purchases comparative to the cost of maintaining a credit card (Reserve Bank of Australia 2021). According to a survey by the Australian Securities and Investment Commission (ASIC), one individual even highlighted that they felt a "false sense of security" using BNPL services for items they would have been more hesitant about purchasing in the past (ASIC 2020). BNPL has targeted the millennial and Generation Z demographic by offering an innovative digital platform whereby individuals can make interest free instalments on in-store and online purchases. Survey results from ASIC showed that customers were agitated by other lenders' personal questions while 'pay later' businesses were approving substantial credit amounts through "very easy" online processes. The 'pay later' business model is driven by allowing customers to own an item immediately but pay for it in

[2] (CBA 2021): https://www.commbank.com.au/articles/newsroom/2021/03/commbank-unveils-bnpl-offering.html
[3] An millenial is known as being born between 1981-1996. The oldest of these individuals would be in their mid-20s to late 30s in 2021 (Dimock 2019).
[4] An individual belonging to Generation Z is known as being born after 1996. The oldest of these individuals would be in their mid-20s in 2021. (Parker & Igielnik 2021)

instalments with no loan like characteristics attached. Some BNPL companies have created an integrated system that performs real-time fraud and creditworthiness assessments (Afterpay 2021).

With BNPL platforms having a propensity towards credit offerings, this research explores the effect of public BNPL company operations on credit lending in Australia and Australian banks. The BNPL companies taken into consideration are Afterpay, Zippay, Payright and Laybuy[5]. To accomplish this, I use time-series regression analysis to extract the effect of BNPL sales and customer numbers on Australian credit card transactions as a whole. Additionally, to isolate the impact on the banking industry, I run a fixed-effects panel regression with five banks that are the most significant contributors to the bank credit lending market. These banks are CBA, Westpac Banking Corporation (WBC), Australian and New Zealand Banking Group Limited (ANZ), National Australia Bank (NAB) and Citigroup Pty Ltd (CPL), which make up 95% of the banking credit lending market[6]. Both unique datasets were manually constructed and have not been used at a collective capacity in prior research. As an extension to the main results, I conduct a time series regression focusing on the E-commerce markets and online retailing due to the recent pandemic causing shifts in consumer spending.

I find that the entrance of BNPL services has negatively impacted the credit lending industry as a whole. For example, for every \$1 million earned in BNPL sales revenue, credit card transaction value decreases by almost \$6 million. Furthermore, spurred by online retailing, results show that after the introduction of COVID, the previous figure has essentially doubled, highlighting a decrease of almost \$11 million in credit transaction value for every \$1 million made collectively by BNPLs. Moreover, as BNPL unique customer additions are on average 500,000 per quarter, this would result in a credit transaction value decrease of approximately \$40,000.

Looking through the banking lens, I find that with a 1% increase in BNPL sales, the ratio of bank credit cards to total bank loans issued decreases by almost 3%. When testing the BNPL sales effect on bank credit cards as a ratio to total assets instead, this effect is more than doubled, resulting in an almost 9% decrease. I also conduct a study using Afterpay online sales data[7]. By isolating the E-commerce debit and credit market, I find that Afterpay sales individually decrease credit transactions made through online platforms whereby credit card details are entered to make payments. In this analysis, I also uncover that credit spending online has increased during Sydney and Melbourne

[5]These companies were chosen on the basis that quarterly data could be sourced and/or calculated from their annual, half yearly and quarterly reports.

[6] See Figure 1.

[7] Other company online sales data was unavailable.

lockdowns. In contrast, Afterpay sales during COVID have reduced credit transactions by almost 0.3% for every 1% increase in Afterpay sales.

I implement a two staged least squares (TSLS) regression using Google Trends data as an instrumental variable for robustness. I use the average mention of each BNPL company's name to garner results similar to that of the original country analysis. The results highlight a $1 million increase in BNPL sales causes credit transaction value to decrease by $13 million.

Despite its importance, we know little about the interactions between fintech players and incumbent financial service providers. This research is essential to dissect how BNPL fintechs are altering the behaviour of lending institutions and, more prevalently, are causing a change in credit usage. I have undertaken this research because it is vital to uncover the impact of BNPLs on the banking industry. With the looming possibility of banks not adopting BNPL processes, there is reason to believe that the credit card sector will reach obsoletion within the decade. It is unobscured that credit card usage is declining, but what is the reason for this? Solely BNPL or something else? While multiple banks are reluctant to lose their footing in the financial sector, the BNPL market has seen partnerships, joining banks and BNPL merchants.

This thesis contributes to the beginnings of research literature in this area. While the RBA and ASIC have conducted statistical descriptions of BNPL data, there have not been any empirical investigations made into the emerging BNPL market as of yet. Perhaps the main contribution of this paper is to begin a dialogue on a topic gaining popularity in a digitally run world where consumers value accessibility and efficiency. In this thesis, I investigate the impact of BNPL in terms of sales, customer acquisition, and online retailing on the Australian holistic and bank credit lending market.

The results of this paper are beneficial to countries, developed or developing, that may be experiencing a similar innovative disruption in their credit lending market. Additionally, with known banks like CBA, NAB and Citigroup creating BNPL products, it goes without saying that banks would not be developing whole new sectors if BNPL did not have the potential for detriment. These banks have altered their operations because consumers are turning to other sources of finance. It is currently impossible to compare the efforts of BNPLs and banks 'pay later' schemes, but studying the effect of such BNPL companies on the Australian lending market is the first step in this area. Market players and consumers alike can better understand the nuances of emerging BNPL fintechs that are essentially at the forefront of disruptive innovation in our time (Sawatzki 2020). Using the datasets mentioned above, I seek to generate results that can benefit stakeholders such as banks, BNPLs and specifically, other countries experiencing a similar surge in fintech operations. I create a foundation for novel research into a new industry that has seemingly manifested itself in the daily functioning of the average Australian (Fisher et al. 2021).

This thesis is showcased as follows: In Section 2, I detail the existing lending literature and critical movements in the BNPL sector as well as my hypothesis development; in Section 3, I present the data collection with descriptive statistics; Section 4 highlights the methodology, results with limitations and future research briefly explored; in Section 5 I conclude.

2. Literature Review

In this section, I will present various literature sources, statistics and general information surrounding BNPLs. Specifically, I will highlight the fintech boom, the current placement of BNPLs in the market, their connection to banks, the drawbacks of this sector and some regulatory issues.

2.1 Introduction to Fintech Boom in Recent Years

Today's market is characterised by high frequency and algorithmic trading (Arnet et al., 2019). This transformation from a paper-based physical system to a digitalised process was encouraged by the interaction between major market players – investors and regulators – aiming to improve efficiency and reduce the risk of market collapses. Furthermore, it should be noted that this prevalent computer trading is conducted with humans as minority participants that are likely to not interact outside the digital sector.

In exploring the positive effects of utilising innovative technology, Arner et al. (2017) examine the impact of financial and regulatory companies on today's culture. They highlight that regulation post-global financial crisis (GFC) helped advance fintech companies. Additionally, as financial services are an effective tool for spearheading economic development, policymakers are constantly seeking methods to support developing countries. With the increasing availability of 'smart' technology, digital financial services have a reasonable opportunity to market their products to the vast population. The combination of unmet demand and network availability has provided countries, especially in Africa, with a chance to realise strong economic growth and financial inclusion.

Fintech startups are vital players in the market today, using financial services and technology to benefit the average consumer. They are addressing challenges and exploring gaps in the market that perhaps traditional lenders like banks have not. The effect of this exploration can be seen in Cornelli et al. (2019), whereby the author highlighted how alternative sources of credit had become more widely used, reaching a value of 800 billion USD globally. Contributing to this figure are developed and developing markets alike. The two most important factors which drive these innovations at the core of financial services are data processing and telecommunications. Both developed and emerging countries have used such tools to encourage the transformation of market players in the industry, thus causing an eruption of lucrative, game-changing innovation.

2.2 BNPLs in the Current Market

It is known that individuals have always had the opportunity to purchase products by paying instalments and have even been able to buy more expensive items through interest-free schemes at specific retailers (Fisher et al. 2021). However, a new system of payments in BNPL has infiltrated the financial sector and snowballed since its creation. Companies that employ BNPL services can generate substantial profits through a factoring method, essentially purchasing 'debt' from merchants and having consumers make instalments directly to them. In Australia, there were more than 6.1 million active BNPL accounts at the end of the 2018/19 financial year, according to a review by ASIC (ASIC 2020). These active account holders made up almost 30% of the adult population of Australia. At this time, approximately 56,000 merchants had implemented BNPL payment options into their business operations.

The number of merchants that offer BNPL options in-store and online has significantly increased in recent years and has almost doubled from 2019 to 2020 (Fisher et al. 2021). In light of the COVID-19 pandemic, the BNPL market has seen a surge in online spending. BNPL services are especially gaining traction in the online fashion retail sector, in which companies do not have brick and mortar stores. The RBA, in attempting to comprehend the consumer behaviour fuelling BNPL decisions, gathered customer data to gauge the importance of merchants having BNPL as a payment option. Around a quarter of individuals believed that BNPL options are essential for small and large online and in-store purchases. In contrast, the remaining majority determined that alternative options like credit cards and PayPal were important. However, when asking individuals who had used BNPL platforms at least once in the last year what their course of action was when a merchant did not offer BNPL, the most cited answer was that they would use debit cards. Furthermore, when the same individuals were questioned on their stance regarding a hypothetical 4% surcharge on a $100 BNPL payment, 10% of users would cancel the payment while the remainder would either switch payment methods or pay the surcharge.

A study by Agrawal and Gentry (2020) conveys that debit cards are a contender for the attention of the millennial demographic. The authors highlight that 70% of millennials preferred debit cards to credit cards. Thus, Agrawal and Gentry ask the inherent question, why would one choose credit over debit when the former, if used advantageously, is essentially a way to buy now and pay later in its own right? The authors aim to fill a gap in the research by examining the psychological determinants for choosing debit cards or credit cards. To highlight the mentality of an average consumer, Brito and

Hartley (1995) show that consumers who wind up paying high interest rates on credit cards will continue to use them as a payment option. Still, if used correctly, Agarwal and Gentry aim to understand why individuals pay immediately, overlooking the benefits apparent with deferred payments. They used a grounded theory study to explore consumer motivation affecting payment-timing decisions, consistent with previous literature. Data consisted of open-ended interviews with 25 participants ranging from ages 23 to 65 and above, with almost an equal number of males and females. All individuals owned both debit and credit cards, with more than half having a proclivity towards using debit cards. The users of credit cards were generally older and were receivers of higher incomes. Furthermore, research has shown that debit card users are often associated with low credit scores and may not qualify to gain access to a credit card (Zinman 2009).

Evidence shows that demand for traditional credit products is plateauing, and according to ASIC, the BNPL sector is experiencing rapid growth (ASIC 2020). The total sum of credit supplied through BNPL doubled from the 2017/18 financial year to the 2018/19 financial year. It is clear that BNPL fintechs are changing the way the finance sector operates. In this thesis, I highlight this notion of BNPL exploring a gap in the market by showing the effect of its popularity on the credit issuance of the Australian credit lending market.

While BNPL payments have increased over recent years, the RBA determined that these purchases still made up only 2% of the total debit and credit card sales in 2020. In comparison, overall debit and credit card spending increased by approximately 11 per cent between 2017/18 and 2019/20. However, as ASIC suggests that credit card issuance is plateauing, most of this increase is likely attributed to debit card sales. Nonetheless, the consumer payments survey (CPS) in 2019 also highlighted that a smaller number of purchases were made through BNPL than other methods, even though it had doubled from the previous year. This information suggests that the impact of BNPL fintechs may not be market altering. Still, it remains essential to uncover the relation between BNPL fintech operations and credit lending in Australia so conclusions on further trajectories can be made.

In search of an answer, Jagtiani and Lemieux (2018), in their paper on underserved credit areas, consider alternate sources of securing financing in light of a potentially fintech-altered market. They underline that bank credit cards are a comparable product to loans given by fintech companies since they are an easily accessible form of unsecured debt. This paper explores the more traditional fintech companies: fintechs that simply provide peer to peer loans or other forms of financing with loan-like characteristics. Their regression model considers whether fintech firms are addressing credit needs in various underserved geographical areas. By controlling for factors like average income, and other environmental variables, they find that an American fintech lending firm, LendingClub, has reached consumers in underserved areas by providing credit where credit availability was low. Through this paper, it can be hypothesised that geographical location would also impact access to credit in Australia, and people may then turn to BNPL platforms. It is clear that fintechs are changing how consumers secure financing; therefore, I aim to understand how this additional avenue of securing funds fairs against holistic Australian credit lending.

2.3 BNPLs and Banks

The concept of a possible threat to banks is conveyed in a paper by Temelkov (2018), whereby the author claims that emerging fintechs are essentially a competitor in the financial sector. They offer similar products and have a looser regulatory framework proving to be a cost advantage to fintechs (Dahl et al. 2016). Traditional banks are also subject to compliance with a corporate hierarchy and a consequently bureaucratic work environment as well as a higher degree of operating costs (Cerqueiro et al. 2009). Fintech firms usually incorporate a more relaxed business culture, often not even implementing a strict organisational ladder.

The impact of the fintech threat to banks can be witnessed in the U.S banking sector, as the industry has experienced a consolidation of active banks, with numbers decreasing from roughly 7500 to 6500 (Korn & Miller 2016). Alternatively, the American fintech sector has seen extreme growth, with financing increasing from $1000 million to $3000 million in five years since the GFC (Gelis & Wood 2014). Although fintech firms are gaining only a small percentage of the market share relative to banks, their rapid growth and innovative ideas spur the notion that they are the most imposing competitor banks will face in the future (Temelkov 2018). The central gap that fintech companies find inherent within the financial sector arises from the fact that banks have strict regulations, as mentioned before (Drummer et al. 2016). This limitation has caused a substantial decrease in customer base and profits.

Interestingly, as the COVID-19 pandemic-initiated lockdowns in major cities like Sydney and Melbourne, big Australian banks have also claimed a collective closure of 350 branches across the country (Frost 2021). A significant trigger for such closures stemmed from heavily declining foot traffic in once busy areas and a surge in online banking. However, Julia Angrisano, national secretary of the Finance Sector Union, claimed the ‘digital shift’ had been overexaggerated by banks. She believes senior managers are using the pandemic as a segue for “cutting costs and overheads” for “fat bonuses”. Furthermore, while banks believe that the acceleration towards online banking has occurred at a faster rate than expected, individuals in regional communities are anxious to begin using digital alternatives due to poor internet reception (Gregory 2021). In the case of rural areas, it is essential to note that neither banks nor BNPL services would have a physical presence there, as, without accessibility to a good internet connection and affiliated merchants, BNPL services are obsolete. In areas where BNPL is accessible, it is logical for banks to close branches, reduce their overheads, and gather customers online to level their costs with BNPLs. In saying that, however, banks risk forgoing the loyalty of older individuals that are unable or unwilling to be part of the 'digital shift'.

As banks aim at levelling the field with BNPLs, there have been new developments in the sector: offerings by licensed credit providers. In a bid to keep up with the uphill trend of BNPL services, CBA announced their product in 2021 after partnering with Klarna, a BNPL company (Eyers 2021). 'CommBank BNPL' will allow 4 million CBA customers to pay for products in 4 instalments, similar to Afterpay. However, analysts believe that CBA may not be able to overtake market leaders like Afterpay and Zip Co due to their late entry into the sector. Additionally, CBA claimed they would not charge merchants more than current card payment fees when accepting the instalments, which could be a major advantage. Regardless, analysts are still unsure whether CBA can outrun BNPL fintechs whose marketing techniques are a catalyst for increasing merchant sales substantially. CBA also aims to triumph over other popular BNPL services by conducting credit checks to lower the chance of customers defaulting on payments and overcommitting themselves. This has been implemented due to evidence that some CBA customers were unable to honour their deferred payments amid COVID-19 struggles. The method is divergent from other BNPL platforms' use of unique algorithms that assess customers' financial risk based on each transaction.

Citigroup has also created an instalment plan using 'Citi credit', which employs the BNPL framework 'but with anything'. Reporter, Michael Rodden, highlights Citi Australia's motive of lowering merchant fees to gain momentum. Merchant fees represent more than 50% of revenue for most BNPLs, according to a review conducted by ASIC (ASIC 2020). Citigroup maintains a similar focus to that of CBA. Contrastingly, ANZ has made a $100 million takeover bid on the small-cap, Cashrewards, an ASX listed company that deals in giving members cash backs on purchases made at specific retailers (Shiffman 2021).

It is evident that banks are threatened enough to change the course of their operations and implement similar strategies to BNPL. This change may aid them in avoiding a similar situation to American banks, but it could be challenging to capture the same hold as giant BNPLs currently dominating the sector. Therefore, it is necessary to highlight a link between the operational characteristics of public BNPL firms and the credit lending of banks if banks have engaged in the climb to the top.

2.4 Drawbacks Associated with BNPLs

While BNPL platforms offer many advantages to consumers, such as low immediate costs and easy access to goods and services, like with all financing solutions, there are drawbacks. These drawbacks consider consumer impulsivity as well as regulatory concerns.

An article aimed at educating individuals on the risks of Afterpay impulse buying highlights essential facts about the inner workings of BNPL platforms, namely the actuality that these services are not legal credit lenders since they do not charge interest. Consequently, they do not have to oblige with specific lending laws (Sawatzki et al. 2020). Furthermore, with lower regulatory costs, there is more space for earning profits. Afterpay generates income through late fees, charging an effective interest rate of almost 30% on purchases not paid for on time. Consumer groups such as CHOICE have shown concern for the concept of impulsive buying and how this may affect the younger generation (Ibrahim and Evans 2020).

Through their Trust Index Report, Deloitte Australia highlights that the younger generation seems to distrust banks (Deloitte Australia 2018). Consequently, a study by ASIC conveyed that 60% of BNPL customers are between the ages of 18 to 34. Additionally, the millennials and Generation Z consumers are anxious about personal debt. They believe that credit cards may be risky and expensive to maintain, whilst having the perception that missing BNPL payments are less risky (Deloitte Australia 2018). The majority of these individuals are primarily students with low incomes, so it is vital to highlight that more than 15% of consumers have incurred a late fee and have counteractively borrowed an additional sum of money to repay a BNPL debt.

Carrying on from a consumer-focused research perspective, Ah Fook and McNeill (2020) explore over-consumption in the digital environment encouraged by BNPL credit. They examine the relationship between impulse purchasing behaviour and BNPL services, specifically reviewing young adult female consumers. They highlight that the younger generation is prone to non-essential consumption and is generally in a fluctuating financial position. The authors used surveys to question a sample of young adult consumers as this demographic has a predisposition towards accumulating debt and is further said to be a key target for BNPL schemes. They find that impulse buying is more potent in individuals who use BNPL services than individuals who do not.

In 2019, Xing, Chen and Zhuang use data from ASIC to investigate how working flow is a cause for financial risk in the BNPL sector. They analyse weights of individual attributes such as gender, location, and occupation to determine why one may default on their payments and thus break their contract with the BNPL company. The authors apply these weights to a logistical model, thereby calculating a probability of default. They further separate the results by age group, gender, marital status, and other features to determine ‘good’ and ‘bad’ clients. Using these results, the authors use an equation to assess the ‘gain value’ of each attribute, that is, the value of the attribute in determining creditworthiness. They have created a precise method of lowering financial risk and accurately predicting default probability in BNPL consumers. Their results show that the greatest ‘gain value’ factors are mortgage, income, and age, while personal factors like characteristics and dependents are less significant.

Thus, it is apparent young consumers with low incomes may be unable to handle the risks associated with using BNPL. However, young people are strong drivers of BNPL popularity. In recent times the millennial generation has been projected to be the largest living adult generation (Bialik & Fry 2019). Therefore, it is crucial to understand how, in anticipation of large demographic shifts, banks and the lending market as a whole may be affected.

2.5 BNPL in the Regulatory View

Consumer protection is a crucial area, especially in the BNPL sector, which essentially comprises debt repayments. To explore this facet of fintech operations, Johnson et al. (2020) assess the impact of low regulation in the fee-based BNPL sector. They highlight that there has been a regulatory failure, most predominantly in the region of consumer protection. Consumers with minimal financial knowledge who may not understand BNPL processes' complexities should be considered and protected in the market. The authors argue that regulations should be implemented through a behaviourally informed approach to benefit the market and ensure sustainability.

To counteract the risks associated with low consumer protection when engaging in BNPL arrangements, ASIC has highlighted a possible regulation intervention to ensure good consumer outcomes (ASIC 2020). While BNPL is considered unregulated under the National Credit Act of 2009, they are regulated under ASIC as credit. Therefore, BNPL businesses will be liable through ASIC’s intervention power, which focuses on consumer outcomes and issues instead of creating a compliance obligation for BNPL companies.

Policymakers have raised another critical issue surrounding BNPL. The RBA highlight that although using innovative technology and increasing competition can allow payment efficiency and fulfil the needs of end-users, it also has the drawback of causing issues for policymakers (Fisher et al. 2021). A significant problem for them when aiming for payment efficiency is that the cost to merchants for accepting BNPL payments is higher than taking other forms of payment. The majority of BNPL companies have also instilled a ‘no-surcharge’ rule that inhibits merchants from passing on this cost to consumers using BNPL services to their advantage. United Bank of Switzerland (UBS) analyst, Tom Beadle, claimed that per his long-held view, the RBA would soon implement regulations to go beyond BNPL 'no surcharge' rules and stunt the growth of the innovative giants (Eyers 2021).

It seems that regulatory issues may cause the growth of BNPLs to slow if changes are implemented. As of yet, no alterations have been made to the framework, but it seems that if the 'no surcharge' rule is removed, BNPLs will forgo a key selling point of their business model, and perhaps credit cards will become more used.

2.6 Hypothesis Development

The world has changed, both socially and technologically, and BNPL fintechs have taken advantage of this. As ASIC and the RBA have highlighted, the younger generation still misuses advantageous features of BNPL transactions like its convenience and low-cost access to short-term borrowing. Credit cards and banks and distrusted due to expensive upkeep, but consumers are unaware of BNPL risks. Banks are contemplating claiming the digital credit sector with their offerings, but analysts believe it is unlikely. The addition of pending consumer protection arrangements and surcharge issues conveyed by regulatory authorities shows that BNPL has drawbacks. Still, banks have also fallen behind in the credit sector, with mostly the older generation or financially stable individuals choosing to use credit cards over other forms of payment. There may be various reasons for the plateau of the credit card sector, but the BNPL sector is a strong contender, in my view, due to its large consumer base and determination to reinvent the industry.

Based on my understanding of the literature, I hypothesised the following:

H1: BNPL sales and customers have a negative effect on credit card lending in both country and bank level analyses. This will depict the shift away from consumers using credit cards but instead using BNPL services as a source of finance.

H2: Debit card transactions have a negative effect on credit card lending. Debit cards are an additional contender to credit payments; therefore, the analysis may depict consumers choosing debit over credit, possibly more so than BNPL.

H3: BNPLs services negatively affect the E-commerce credit market. With online spending rising throughout Australia and BNPLs target marketing their payment strategies through digital sources, the analysis will show online Afterpay sales negatively impact online credit card sales.

3. Data

In this section, I describe the data collection, scaling and transformations. Section 3.1 describes the dependent variables used in this study, section 3.2 outlines the main test variables, section 3.3 highlights the control variables, and section 3.4 presents some descriptive statistics of the variables analysed.

3.1 Credit Cards

The dependent variable of interest in the country level analysis is the total credit card transaction value. This value takes into consideration all bank and non-bank issued credit purchases that are domestic and overseas, considering contactless payments made using devices as well. These data are sourced through the RBA payments statistics[8]. I have chosen, specifically, the data which has been adjusted for seasonality. Using this data provides a high-level view of the current lending situation across Australia. Furthermore, to enhance the information embedded in these data points and scale the data, I take credit transaction values as a percentage over total spending. Total spending is proxied by summing credit, debit, BNPL and cheque transactions[9]. These data are taken at quarterly intervals and range from 2015 – 2021. This variable has seen a decline in recent times, as seen in Figure A.1 (see appendix).

In the bank level analysis, the key dependent variable is the balance sheet item of Loans to Households: Credit Cards for each bank. This is the gross value of credit card liabilities by Australian households in various banks, including international banks, ranging from 2002 to 2021. This data is sourced from the Authorised Monthly Deposit-Taking Institution Statistics through the Australian Prudential Regulatory Authority (APRA)[10]. This dataset was most suitable as it provides select financial information on the banking activities of a significant number of individual banks through their interactions with the domestic market. The variables within this dataset are all balance sheet items and are in millions of Australian dollars (AUD). The nature of this variable, in that it is a level item, allows me to extract the necessary figures from 2015-2021 at quarterly intervals to match against the available BNPL data. To scale this variable and allow the results to be more informative, providing a better indication of how credit lending is affected, for the bank-level analysis, the dependent variable 'Loans to Households: Credit Cards' will be placed as a

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[8] (RBA 2021): https://www.rba.gov.au/payments-and-infrastructure/resources/payments-data.html
I specifically looked at C1.

[9] The total spending amount includes types of payment options that can be substituted for BNPL services and vice versa. Cash has not been included due to data unavailability.

[10] (APRA 2021): https://www.apra.gov.au/monthly-authorised-deposit-taking-institution-statistics

fraction of total loans. Using an alternative dependent variable, I will also scale credit card loans by total assets as a robustness check.

3.2 BNPL Operations

One of the independent variables is the sales transaction volume of four BNPL focused fintech companies[11]. These companies are Afterpay, Zippay, Payright and Laybuy. Using the sales figures from each company, a total sales value was calculated by summation, with the collected data spanning seven years (2015-2021) at a quarterly frequency. The figures in this data are in millions of AUD. One company, Laybuy, reported its annual reports figures in New Zealand Dollars (NZD) and this was converted appropriately using NZD/AUD historical exchange rates sourced from APRA. In case specific quarterly data could not be found but was necessary for inclusion due to its substantial contribution to the summation, interpolation techniques were utilised. For example, if semi-annual data for December 2016 was available, but not for the September 2016 and December 2016 quarter separately, the average proportion among September quarters was derived before and after the missing year, and this proportion was applied to the semi-annual figure. After accounting for all missing values in this manner, I find that there is an extensive range of values, with the first being one million and the last being almost four thousand million. Therefore, to scale the variable in the same way as the dependent variable of credit card transactions, I use BNPL sales as a ratio to total spending for the bank and country analysis. It is important to note that these data have been adjusted for seasonality manually (Hood 2017)[12].

The other independent variable in focus is the unique customers acquired by the four BNPL focused companies mentioned above; Afterpay, Zippay, Payright and Laybuy[11]. Quarterly data of customer number changes are given in quarterly reports as well as half-yearly reports. These numbers were taken, and the customer number at time t -1 was taken for each period to gather unique customers added. Data surrounding customer numbers could not be sourced earlier than December 2016 compared to the BNPL sales data that I extracted manually from March 2015 onwards. Similar interpolation techniques were used to the averaging method used above, specifically for Afterpay data, as the company comprises a significant portion of the BNPL total

[11] Data source: quarterly updates, business updates, investor presentations, half-year reports, yearly reports all gathered from https://www2.asx.com.au/markets/trade-our-cash-market/historical-announcements by entering ASX code, perusing all reports and hand collecting relevant figures.

[12] I first create a regression using the BNPL sales data (y) with an "index" (1,2,3…) (x) and then calculate the trend for each data point using the regression equation whereby y = Intercept + BNPLsales*index. I then find the difference between the original data point and the calculated number to show the residuals. The seasonal factor is the average of the residuals for each given quarter. This seasonal factor is subtracted from the original series, returning the seasonally adjusted sales values for each quarter.

consumer base. Furthermore, to easily interpret the data and because of the variation in numbers, I perform a log transformation on BNPL unique customers. This transformed variable is used throughout the analysis.

3.3 Control Variables

3.3.1 Macro-Level Controls

In Zinman's journal article surrounding the debate of 'debit or credit?', he emphasizes that debit cards can offer similar features to credit cards in terms of acceptance, security portability and time expenses. The crucial attribute to differentiate one from the other is the marginal cost attached to credit cards. The results of the study highlight that 'revolvers' – individuals that keep a credit balance and pay it off over time – are more likely to use debit. Overall, Zinman shows that debit cards are becoming a more substantial substitute for credit. This is the reason behind adding debit card transaction values as a control to this experiment. I must account for the effects of debit substitution also altering the levels of credit lending. These seasonally adjusted data are sourced through RBA payments statistics and range from 1985 to 2021[13]. As I required data at quarterly intervals to match the BNPL sales data collected, debit card transactions were summed at quarterly intervals to record one figure per quarter. This variable is also scaled by total spending, uniform to credit card transactions and BNPL sales.

Credit limit as a control is essential to implement. Soman and Cheema (2002) argue that individuals use credit limits as a "signal of their future earnings potential". They highlight that should consumers have access to large amounts of credit, they will likely spend significantly more, believing their lifetime income will be substantial. They prove this hypothesis after using a plethora of investigative analyses, finding consistency in the results – higher credit limits lead to more spending, especially if the credibility of the limit is increased. Therefore, it is apparent that credit limits affect expenditure and, consequently, the key dependent variable. This variable is sourced from RBA payments statistics, whereby the data ranged from 2002 to 2021[14]. To appropriately use this variable as a control within the country level analysis, I take the percentage change of credit limit at each quarter ranging from March 2015 to June 2021.

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[13] (RBA 2021): https://www.rba.gov.au/payments-and-infrastructure/resources/payments-data.html
I specifically looked at C2.

[14] (RBA 2021): https://www.rba.gov.au/payments-and-infrastructure/resources/payments-data.html
I specifically looked at C1.2.

3.3.2 Bank-Level Controls

This section details the controls found explicitly in the APRA dataset as balance sheet items associated with each bank in question. Furthermore, the controls listed in this section are only used in the bank-level analysis.

As Berger et al. (2001) show that using total assets to control for bank size is optimum, I will proxy this measure using the 'Total resident assets' variable. This refers to all assets on the banks' domestic books that are due from residents. Additionally, Berlin and Mester (1999), in their paper regarding the exogenous effect of credit shocks on borrowers, highlight log of bank size specifically as a variable that can proxy for scale-related sections of lending costs. Therefore, I perform a log transformation on this variable which is used in the bank analysis. This data is taken at a quarterly frequency from March 2015 to June 2021.

Berlin and Mester (1999) highlight the usage of the loans to deposits ratio in their paper, focusing on how banks' access to inelastic rates consequentially allows them to insulate their borrowers against exogenous credit shocks. They notice that high loans to deposits and low equity to assets ratios correlate with riskier portfolio strategies. Loans are the 'total gross loans and advances' available in the APRA dataset, defined as the summation of loans to financial corporations, non-financial corporations, and households. Deposits are the 'total deposits' also available in the APRA dataset as a bank-specific variable. They are defined as the sum of transaction deposit accounts, non-transaction deposit accounts, certificates of deposit and foreign currency deposits. I calculate this ratio at a quarterly frequency from March 2015 to June 2021.

3.3.3 Binary Controls

In Late 2019, when COVID-19 first began hitting news and media outlets, the effect and scale of the disease were uncertain (Borges 2020). However, as 2020 arrived and the world entered a state of the pandemic, the detrimental impact of this disease could be seen in each nation's economy. Australia suffered a recession towards the end of 2020, and the government introduced stimulus packages to aid communities, workers, and households to retain stability. Considering this pandemic and its effects on the country's fiscal stature, I have implemented a binary variable where 0 represents time periods before COVID emerged and a value of 1 is implemented at the end of 2019 and onwards for when COVID first emerged as a known disease (World Health Organisation 2020).

When the first restrictions were placed on Sydney communities during mid-2020, online sales rose exponentially (ABS 2021). This upheaval in web purchases allowed for a further surge in BNPL usage. Deals, discounts, and events made way for consumers to purchase products from home, whereby this product was delivered straight to their doorstep with lowered concern for pandemic related misfortunes. Due to this change, which was reignited in the 2021 almost four-month long lockdown from July to October, there is reason to believe that the lockdowns/restrictions would negatively impact credit lending. This binary variable was manually implemented by assessing the periods of lockdown or restrictive measures executed in Sydney using government announcements (Storen & Corrigan 2020); (NSW Health 2021)[15]. This variable represents restrictions as 1 and no restrictions as 0.

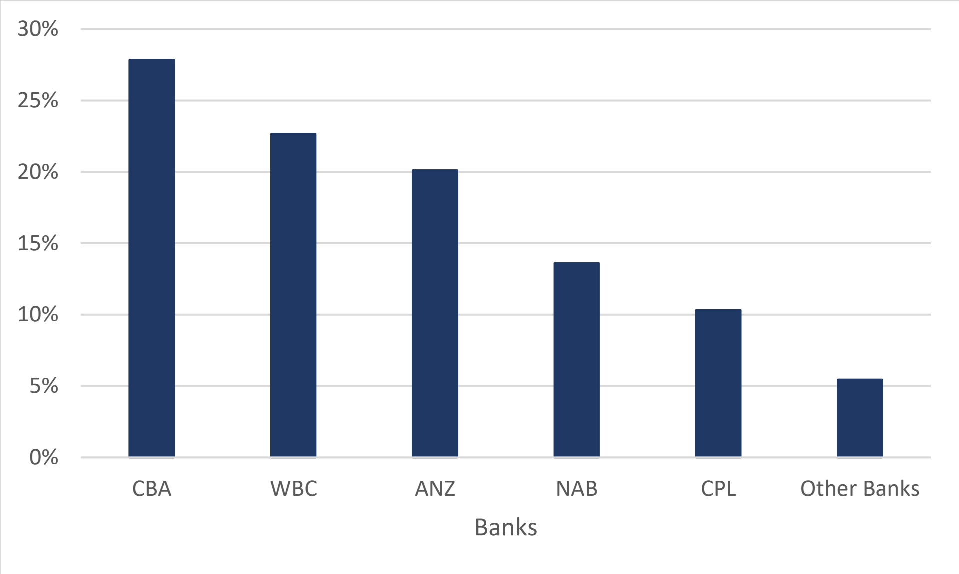
Another Australian city, Melbourne, experienced the most prolonged lockdown in recent history out of all the world's cities following the pandemic (Burgess & McKay 2021). Analogous to the binary variable described above, I also implement a *Melbourne Lockdown Dummy,* which focuses on times when Melbourne was placed under a lockdown or restrictive measures using government announcements (Storen & Corrigan 2020); (NSW Health 2021). This will similarly be an indicator of changing spending habits as households in Melbourne were less mobile. This variable represents restrictions as 1 and no restrictions as 0.

3.4 Descriptive Statistics

Five banks were chosen on the basis that their contribution to the holistic credit lending market was the greatest. In selecting the appropriate banks to implement in this study, it was essential to uncover each bank's contribution to the overall credit card lending within the dataset. To ensure the banks evaluated were entities affected in recent times by the surge of BNPL as well as the pandemic, I took balance sheet figures for 'Loans to Households: Credit Cards' as of June 2021 summed the figures and calculated the percentage contribution of each bank. As most banks made up 0 to 1 percent of the credit market, I aimed to include larger banks. The banks of interest in this study are Citigroup and the big four Australian banks, ANZ, CBA, NAB and WBC. The banks I have chosen for the panel data analysis collectively comprise 95% of the bank personal credit lending market, as seen in Figure 1.

[15] Government information on COVID situation: (Storen & Corrigan 2020); (NSW Health 2021).

FIGURE 1: PERCENTAGE CONTRIBUTION OF BANKING CREDIT LENDING MARKET

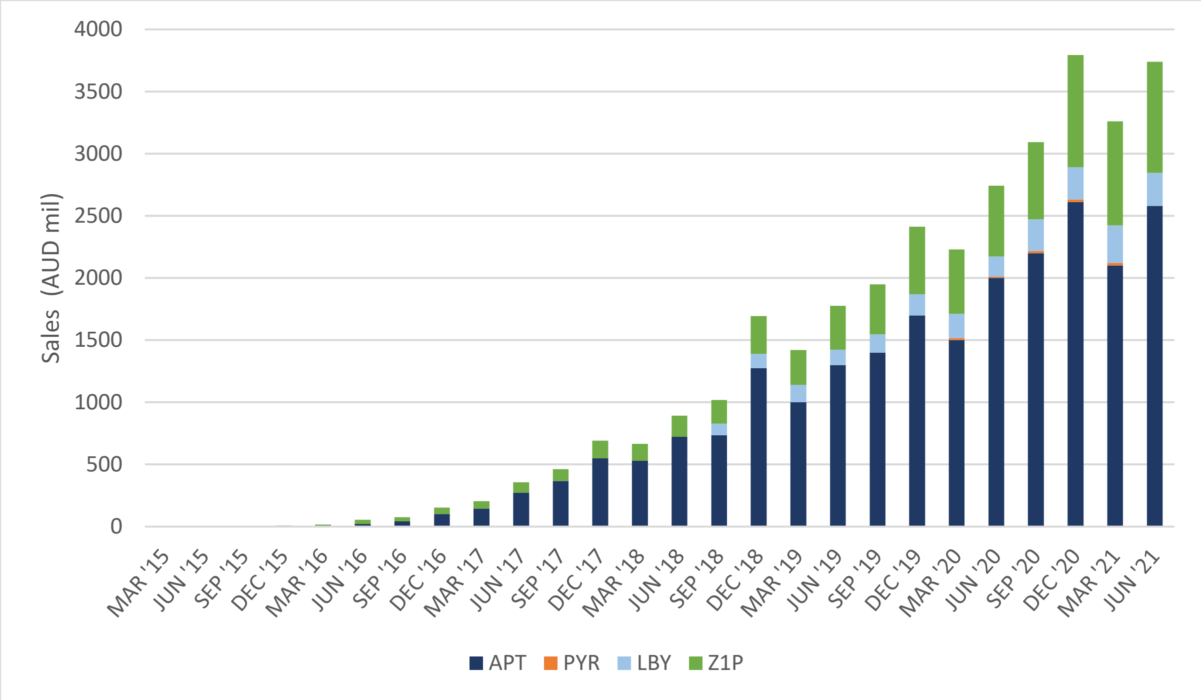


Notes: Figure 1 shows the percentage contribution of the banks analysed in the credit lending market, with CBA leading at almost 30%.

The BNPL companies were chosen due to their higher level of transparency in annual reports, with figures split by regions around the world. Afterpay, Zippay, Laybuy and Payright, after a thorough investigation, were noted to be the most transparent in publishing quarterly financial statistics[16]. Some companies, like Afterpay, Zippay and Payright, began in Australia and only started venturing out into the global market after a few years. In their initial financial reporting, all figures were subject to Australian consumers only. However, as the business expanded and became a more prominent BNPL provider, reported figures changed. What began as Australian reported figures changed to Australia and New Zealand summed sales. Laybuy included Australian and New Zealand figures from the beginning, which I recalculated using historical exchange rates. Figure 2 shows the raw sales data of each BNPL company. Here, it is clear that Afterpay dominates the sales sector, perhaps due to it being one of the first entries into the market. Zippay also contributes a substantial share, especially in recent times, with Laybuy and Payright having relatively small additions.

[16] It was important to find companies which listed quarterly statistics or semi-annual statistics which quarterly data could be calculated through.

FIGURE 2: LISTED BNPL COMPANY SALES MARCH-2015 TO JUNE-2021

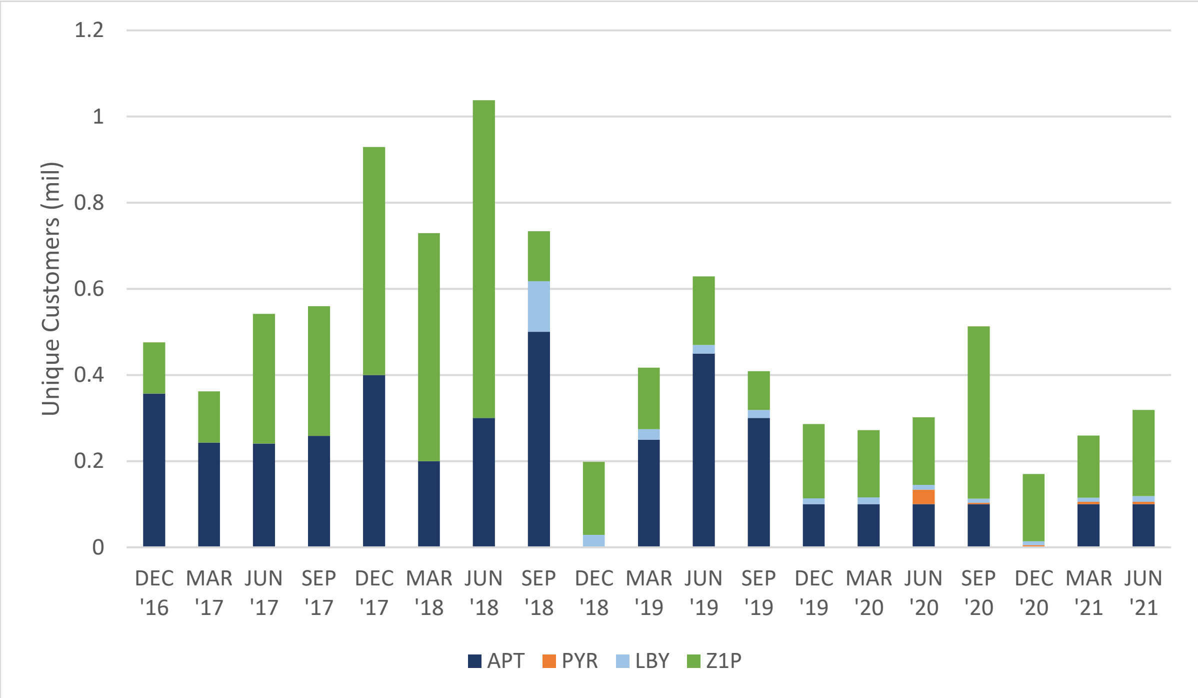


Notes: In Figure 2, Afterpay (dark blue) can be seen as the dominant company in terms of sales contributions, further highlighting the importance of interpolating figures for missing data. This is raw data taken from company reports – the data used in the analysis has been adjusted for seasonality.

It is important to note that the figures I have included in my analysis also depict data from New Zealand transactions. While companies are required to list certain figures, splitting up the sales by Australia and New Zealand is not often seen. However, business environments between Australia and New Zealand have been monitored under a Single Economic Market (SEM) strategy (NZ Foreign Affairs and Trade 2021). This strategy aims to provide an interchangeable trans-Tasman market that allows Australian consumers and businesses to just as easily transact and operate in New Zealand and vice versa. For this reason, I find it appropriate to have used summed figures to provide information on BNPL sales.

Similarly, Figure 3 shows the unique customer additions for each BNPL company individually, Contrastingly, it is clear that while in sales, Afterpay is dominant, Zippay contributes a substantial amount to unique customers added per quarter. Laybuy is a minor contributor with data availability beginning in 2018, and Payright is also dominated by the other giants from June 2020 onwards. Furthermore, it seems that while the companies were in their growth era, customers added were significant. Comparably, as the companies enter maturity, figures begin to plateau and even decrease considerably at the time of the emerging pandemic in late 2019.

FIGURE 3: LISTED BNPL COMPANY UNIQUE CUSTOMERS



Notes: In Figure 3, Zippay can be seen as the dominant company in terms of customer additions.

In Table 1, I have displayed summary statistics of each variable in the form it was used throughout the analyses, at both the country and bank level. In Table A.3 (see appendix), there are extended summary statistics that include original variables before transformations or scaling. It is important to note that stationarity testing was not conducted as ADF and KPSS tests are unlikely to result in accurate results based on the notion that the number of time periods used in the study is small (T<30) (Baltagi & Kao 2001). As the time series variables, such as credit transactions, debit transactions and BNPL sales, have only 26 observations, it would not be helpful to conduct such stationarity tests as Cochrane (1988) argues the low testing power of ADF and KPSS checks. Additionally, in order to avoid spurious relationships between variables, total spending[17] is used to scale credit, debit and BNPL transactions while credit limit is analysed in percentage changes. The remaining variables, CreditCards/Loans, CredtCards/TotalAssets and Loans/Deposits are either scaled by another variable or already in percentage form.

In Table 2 and Table 3, I have shown the Pearson's correlation matrix of the country level and bank level variables, respectively. There are some overlaps between the two tables. I recognise and acknowledge that debit transactions seem to have a high correlation with credit transactions and BNPL

[17] Total spending = total value of credit transactions + total value of debit transactions + total BNPL sales + total value of cheque transactions

alike. Perhaps, this is because they are all interconnected and directly relate to each other through payment making necessities. In Table A.4 (see appendix), I run a regression excluding debit cards and highlight that it is an important variable to include economically. The exclusion of this variable results in an omitted variable bias in the BNPL sales coefficient. Credit limit and the binary controls have reasonable but not excessively high or low correlations with the primary variable of interest. Importantly, BNPL customers does not exhibit very high or low correlations with controls or dependent variables.

TABLE 1: DESCRIPTIVE STATISTICS OF ALL VARIABLES USED IN COUNTRY AND BANK ANALYSIS

Variable	Obs.	Mean	Std	Min	25%	50%	75%	Max
Credit Transactions*	26	0.2189	0.0420	0.1677	0.1815	0.2069	0.2603	0.2814
CreditCards/ Loans**	130	0.0796	0.1279	0.0081	0.0136	0.0181	0.0222	0.3680
CreditCards/ Total Assets**	130	0.0593	0.1002	0.0049	0.0086	0.0125	0.0156	0.3240
BNPL Sales*	26	0.0041	0.0046	-0.0002	0.0002	0.0020	0.0069	0.0136
BNPL Customers	19	-0.8496	0.5043	-1.7702	-1.2240	-0.8744	-0.5220	0.0374
Debit Transactions*	26	0.2246	0.0840	0.1337	0.1556	0.1950	0.2785	0.3817
Credit Limit	26	-0.4126	1.0674	-2.7208	-1.0689	-0.3201	0.4231	1.1634
COVID	26	0.2308	0.4297	0.0000	0.0000	0.0000	0.0000	1.0000
Sydney Lockdown	26	0.0769	0.2717	0.0000	0.0000	0.0000	0.0000	1.0000
Melbourne Lockdown	26	0.1538	0.3679	0.0000	0.0000	0.0000	0.0000	1.0000
Loans/Dep**	130	1.3603	0.3367	1.0679	1.1783	1.2511	1.2978	2.7333
Total Assets**	130	12.7557	1.4958	9.5720	13.2637	13.4546	13.5632	13.8364
Trends	26	12.9038	12.4387	0.0000	0.2500	11.6250	19.3750	39.5000

Notes: Table 1 displays the descriptive statistics for all variables between 2015 and 2021. Credit Transactions is the total value of credit transactions. CreditCards/Loans is the 'loans to households: credit cards' as a fraction over 'total loans and advances'. CreditCards/Total Assets is the loans to households: credit cards' as a fraction over 'total resident assets'. BNPL Sales is the collective sales of 4 BNPL companies. BNPL Cus is the log of BNPL unique customer numbers of 4 BNPL companies. Debit Transactions is the total value of debit transactions. Credit Limit is the percentage change of credit limits for Australian credit cards. COVID represents a binary variable that shows the existence of the COVID-19 virus. Sydney Lockdown and Melbourne Lockdown are binary variables for times when Sydney and Melbourne were under lockdown/heavy restrictions. Loans/Deposits is the 'total loans and advances' as a fraction over 'total deposits'. Total Assets is the log of total resident assets. Trends is the Google Trends data used as the instrumental variable.
**This variable is analysed as a fraction over total spending*
***Bank-specific variables*

TABLE 2: PEARSON'S CORRELATION MATRIX – COUNTRY LEVEL VARIABLES

	Credit Trans*	BNPL Sales*	BNPL Cus	Debit Trans*	Credit Limit	COVID	Syd LD	Mel LD	Trend
Credit Trans*	1.00								
BNPL Sales*	0.93	1.00							
BNPL Cust	-0.59	-0.61	1.00						
Debit Trans*	0.95	0.99	-0.57	1.00					
Credit Limit	-0.88	-0.85	0.40	-0.87	1.00				
COVID	0.71	0.86	-0.54	0.83	-0.66	1.00			
Syd LD	0.38	0.41	-0.48	0.37	-0.18	0.53	1.00		
Mel LD	0.52	0.60	-0.24	0.59	-0.53	0.78	0.28	1.00	
Trend	0.47	0.23	0.37	0.31	-0.46	-0.06	-0.09	-0.01	1.00

Notes: Table 2 shows the correlation matrix between variables used in the country level analysis at a quarterly frequency from 2015 to 2021. Credit Trans is the total value of credit transactions. BNPL Sales is the collective sales of 4 BNPL companies. BNPL Cus is the log of BNPL unique customer numbers of 4 BNPL companies. Debit Trans is the total value of debit transactions. Credit Limit is the percentage change of credit limits for Australian credit cards. COVID represents a binary variable that shows the existence of the COVID-19 virus. Syd LD and Mel LD are binary variables for times when Sydney and Melbourne were under lockdown/heavy restrictions.
**This variable is analysed as a fraction over total spending*

TABLE 3: PEARSON'S CORRELATION MATRIX – BANK LEVEL VARIABLES

	CC/ Loans	CC/TA	BNPL Sales*	BNPL Cus	Debit Trans*	COVID	Syd LD	Mel LD	Loans/ Dep	TA
CC/Loans	1.00									
CC/TA	0.98	1.00								
BNPL Sales*	-0.02	-0.11	1.00							
BNPL Cust	0.03	0.09	-0.61	1.00						
Debit Trans*	-0.02	-0.11	0.99	-0.57	1.00					
COVID	-0.03	-0.11	0.86	-0.54	0.83	1.00				
Syd LD	-0.01	-0.05	0.41	-0.48	0.37	0.53	1.00			
Mel LD	-0.02	-0.08	0.60	-0.24	0.59	0.78	0.28	1.00		
Loans/Dep	0.84	0.88	-0.23	0.14	-0.23	-0.20	-0.08	-0.14	1.00	
TA	-0.99	-0.97	0.06	-0.04	0.06	0.06	0.03	0.04	-0.87	1.00

Notes: Table 3 shows the correlation matrix between variables used in the bank level analysis at a quarterly frequency from 2015 to 2021. CC/Loans is the loans to households: credit cards as a fraction over total loans. CC/TA is the loans to households: credit cards as a fraction over total assets. BNPL Sales is the collective sales of 4 BNPL companies. BNPL Cus is the log of BNPL unique customer numbers of 4 BNPL companies. Debit Trans is the total value of debit transactions. COVID represents a binary variable that shows the existence of the COVID-19 virus. Syd LD and Mel LD are binary variables for times when Sydney and Melbourne were under lockdown/heavy restrictions. Loans/Deposits is the total loans and advances ratio to total deposits of banks. TA is the total resident assets of banks.

**This variable is analysed as a fraction over total spending*

4. Methodology & Results

The methodology is described in Section 4.1, with country level and bank level results depicted in Section 4.2 and 4.3, respectively. Further, limitations and implications for future research will be explained in Section 4.5 and 4.6, respectively.

4.1 Methodology

Initially, the analysis had begun as solely a panel regression involving banks. However, to show the effect of BNPL on a similar stock variable rather than simply a flow variable like balance sheet items, the methodology expanded to include a country level time series analysis. Furthermore, due to the small sample of data collected, as is expected based on a short time since BNPL inception, the number of control variables was kept to a minimum. The selection of control variables is based on existing literature, as seen in Section 3.3.

Two novel analyses will be used to explore the relationship between BNPL fintech sales and Australian credit lending. To ascertain the overall impact of BNPL operations on credit lending in Australia, I will use a time-series regression model using RBA payments data to carry out the country level analysis. For a more granular view on the credit lending system, I will use a panel regression to look at bank-specific lending through APRA bank statistics in a bank-level analysis. The data are available for a limited period at different frequencies but cover a comparably more significant number of banks and public fintech companies. Panel analysis is, therefore, the most conducive approach.

The overarching models surrounding the country level analysis will use a time-series regression equation. Equation (1) represents the dependent variable as credit card transaction volume, y_t:

$$y_t = \alpha_t + \beta_1 BNPL_t + \beta_2 Debit_t + \beta_3 CrdLim_t + \beta_4 COV_t + \beta_5 SydLD_t + \beta_6 MelLD_t + u_t \text{ (1)},$$

where α is the intercept, *BNPL* is BNPL variables, *Debit* is the total value of debit card transactions, *CrdLim* is the credit limit of credit cards, *COV* represents the pandemic, *SydLD* and *MelLD* represent times of lockdown in Sydney and Melbourne, respectively and *u* is the error term.

In the bank-level study I use a panel data regression. Due to the clustered nature of the APRA banking statistics, it is pertinent to this study that a panel fixed effects regression be used for analysis. Therefore, I will use a panel regression to understand the effect of BNPL Sales on the credit lending of banks. Equation (2) represents the dependent variable as loans to households: credit cards, $y_{i,t}$:

$$y_{it} = \alpha_i + \beta_1 Bank_{i,t} + \beta_2 Debit_t + \beta_3 BNPL_t + \beta_4 COV_t + \beta_5 SydLD_t + \beta_6 MelLD_t + n_i + u_i \text{ (2)},$$

where, α represents bank *i* at time *t*, *Bank* is bank specific control, *Debit* is the total value of debit card transactions, *BNPL* is BNPL variables, *COV* represents the pandemic, *SydLD* and *MelLD* represent times of lockdown in Sydney and Melbourne, respectively, *n* is the bank fixed effect and *u* is the error term.

4.2 Country Level Results

The time series regression results generated for the country level analysis are displayed in Table 4. The first column highlights the control-only regression, which shows all variables besides the Melbourne lockdown dummy as significant at the 10% level. Adding the test variable in column 2 highlights a negative BNPL coefficient, and the control variables remain consistent with column 1, conveying a reasonable R^2 of 0.956 and a low Jarque-Bera statistic.

TABLE 4: COUNTRY LEVEL RESULTS WITH BNPL SALES AS MAIN TEST VARIABLE

Dependent Variable	Total Credit Card Transaction Value				
	(1)	(2)	(3)	(4)	(5)
BNPL Sales		-5.4273	3.4898**	-1.5999**	-0.6886
		(3.839)	(1.6)	(0.688)	(1.17)
BNPL Sales*Covid Dummy			-10.8928*		-1.8248
			(1.148)		(1.871)
Debit*Covid Dummy				-0.6653*	-0.5641*
				(0.03)	(0.12)
Covid Dummy	-0.0528*	-0.0444***	0.0719*	0.1917*	0.1752*
	(0.015)	(0.014)	(0.013)	(0.011)	(0.023)
Debit Transactions	0.5676*	0.8270***	0.5367*	0.8367*	0.7866*
	(0.055)	(0.209)	(0.076)	(0.036)	(0.069)
Credit Limit	-0.005*	-0.0051	0.0006	0.0042*	0.0038*
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Sydney LD Dummy	0.0268*	0.0283***	0.0074*	-0.0011	-0.0001
	(0.014)	(0.010)	(0.002)	(0.002)	(0.002)
Melbourne LD Dummy	0.0185	0.0162	-0.0038	-0.006*	-0.0059*
	(0.015)	(0.011)	(0.005)	(0.002)	(0.002)
Constant	0.0966*	0.0587*	0.0958*	0.0497*	0.0573*
	(0.01)	(0.032)	(0.011)	(0.006)	(0.011)
Observations	26	26	26	26	26
R^2	0.963	0.967	0.996	0.998	0.998
Adjusted R^2	0.953	0.956	0.994	0.998	0.998
Jarque-Bera	1.806	3.697	5.618	1.057	0.556

*Notes: robust standard errors in parentheses; p < 0.1 *, p < 0.05**, p < 0.01****
'LD': lockdown

Economically, the BNPL Sales coefficient highlights that a 1 unit increase in BNPL Sales causes a $5.42 million decrease in credit card transaction values[18]. This satisfactory result conveys the nature of BNPLs rising and the inverse decrease seen in Australian credit lending overall.

To extract COVID specific results at a greater capacity, I proposed to add some COVID interaction terms to the models, adding them one at a time and then together. Table 4, column 3 includes the BNPL and COVID interaction term. This interaction is significant at the 10% level and conveys a larger decrease, almost $11 million, in Credit Transaction Value when BNPL increases by $1 million. Therefore, seeing as how the COVID interaction term has absorbed the negative effect in column 3, it may denote BNPL being detrimental to banks in periods of high stress, high online spending and when individuals are anchored to their homes. Any future possibility of such extreme measures being implemented in Australia could show similar results.

This, coupled with the now positive coefficient of BNPL Sales individually, emphasises that the main load of adverse effects on credit stem from the beginnings of COVID. However, this result also underlines the notion that BNPL itself may not have as strong an influence without the economic power of COVID spurring it on in the homes of consumers. This is not difficult to believe, as the BNPL framework advertises a simple process on a medium that is accessible almost anywhere with reasonable Wi-Fi.

Moving forward, I run the same regressions as shown in Table 4 with a different independent variable; BNPL Customers. The regression results are laid out in Table 5. Columns 1 and 2 remain consistent even with the addition of the independent variable, which is negative and significant at the 5% level. This coefficient remains negative in all models. In column 2, this key coefficient can be interpreted as a 1% increase in BNPL Customers, causing a less than $100 decrease in credit transaction value. For example, as the average number of BNPL unique customers garnered is 500,000 per quarter[19], this would result in credit card transaction value decreasing by almost $40,000[20].

Interestingly, the COVID Dummy can be interpreted as causing an almost 0.05 percentage decrease in credit transaction value as a fraction over total spending. This is likely because spending has lowered after COVID emerged due to lowered mobility (ABS 2021). Based on this significant

[18] As both Credit Card Transaction Value and BNPL Sales are placed as a fraction over the same variable, Total Spend, this interpretation is satisfactory.

[19] Average number of unique customers added across all 4 BNPL companies collectively.

[20] -0.0076/100*500,000=38,000. This interpretation is based on the fact that the BNPL Customer variable is log transformed.

coefficient, the interaction terms of BNPL and Debit with COVID are helpful in further breaking down this relation. Column 3 highlights the BNPL-COVID interaction term, which is negative but insignificant.

TABLE 5: COUNTRY LEVEL RESULTS WITH BNPL CUSTOMERS AS MAIN TEST VARIABLE

Dependent Variable	Total Credit Card Transaction Value				
	(1)	(2)	(3)	(4)	(5)
BNPL Customers		-0.0076**	-0.0051**	-0.001	-0.0011
		(0.004)	(0.002)	(0.001)	(0.001)
BNPL Customers*Covid Dummy			-0.0309		0.002
			(0.024)		(0.005)
Debit*Covid Dummy				-0.684*	-0.6888*
				(0.038)	(0.041)
Covid Dummy	-0.0528*	-0.053*	-0.098**	0.1949*	0.1996*
	(0.015)	(0.015)	(0.04)	(0.014)	(0.02)
Debit Transactions	0.5676*	0.5401*	0.5689*	0.7695*	0.7692*
	(0.055)	(0.058)	(0.061)	(0.022)	(0.021)
Credit Limit	-0.005*	-0.0047	-0.0039	0.0046*	0.0046*
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Sydney LD Dummy	0.0268*	0.0227	0.0133	-0.0026	-0.0022
	(0.014)	(0.014)	(0.017)	(0.003)	(0.003)
Melbourne LD Dummy	0.0185	0.0202	0.0327*	-0.0054**	-0.0064*
	(0.015)	(0.014)	(0.018)	(0.002)	(0.004)
Constant	0.0966*	0.0978*	0.0938*	0.0582*	0.0582*
	(0.01)	(0.01)	(0.011)	(0.004)	(0.004)
Observations	26	19	19	19	19
R^2	0.963	0.941	0.946	0.997	0.997
Adjusted R^2	0.953	0.911	0.912	0.995	0.997
Jarque-Bera	1.806	0.085	0.256	1.572	1.734

*Notes: robust standard errors in parentheses; p < 0.1 *, p < 0.05**, p < 0.01****
'LD': lockdown

The lockdown coefficients remain positive until the debit-COVID interaction is introduced, suggesting that individuals in Sydney and Melbourne were using credit less and debit more during COVID. Furthermore, while Debit Transactions at an individual capacity consistently show positive coefficients, which vary in significance, in column 4, the interaction of debit and COVID suggest a *negative* effect. The original positive impact may stem from the notion of debit cards being payment avenues for credit card management. Therefore, as credit purchases are made, debit payments are given to fund those purchases, even if this is delayed while consumers manage their finances. The negative coefficient of debit transactions in column 4 conveys that debit during COVID does not follow the path of individual debit. But instead, debit transactions are increasing through another avenue; BNPLs. Similar to the way in which debit cards are linked to credit cards, BNPL may also be linked to some type of debit account for making repayments.

Lastly, for robustness and to account for endogeneity concerns whereby credit transaction value may have an effect on BNPL spending since credit cards are an additional source of repayments for BNPL purchases, I have implemented a TSLS regression (Becker 2007). The instrumental variable used is the average “mention” of the BNPL companies involved in the BNPL variables of interest collected at quarterly intervals from March 2015 to June 2021. Due to this variable being time-specific, I have only implemented this instrument in the country level analysis. A 2020 paper written by Gao, Ren and Zhang highlights the use of Google Trends as a means to investigate investor sentiment and its relation to stock price. This platform in which one can extract mentions of a specific term or phrase is seen as highly informative because it reflects the attitudes of market participants in a timely fashion. Importantly, data used in Google Trends is scaled on a range of 1 to 100 based on the level of popularity one topic may have comparative to all other topics. A value of 100 would mean that the subject has reached its peak in popularity, while a value of 50 would suggest that it is half as popular as it was previously.

The results of the instrumental variable regression are laid out in Table 6. Column 1 contains the control variable only regression results. Columns 2 and 4 are the original models without interactions but simply the main test variables, BNPL Sales and Customers, respectively. In this section, columns 3 and 5 are most important.

TABLE 6: COUNTRY LEVEL RESULTS WITH INSTRUMENTAL VARIABLE

Dependent Variable	Total Credit Transaction Value				
	(1)	(2)	(3)	(4)	(5)
BNPL Sales		-5.4273	-13.313		
		(3.839)	(9.5339)		
BNPL Customers				-0.0076**	0.0199
				(0.004)	(0.0218)
Debit Transactions	0.5676*	0.8270***	1.2039*	0.5401*	0.6066*
	(0.055)	(0.209)	(0.4233)	(0.058)	(0.0858)
Credit Limit	-0.005*	-0.0051	-0.0052	-0.0047	-0.0055
	(0.003)	(0.004)	(0.005)	(0.003)	(0.0057)
Covid Dummy	-0.0528*	-0.0444***	-0.0323	-0.053*	-0.0468**
	(0.015)	(0.014)	(0.0226)	(0.015)	(0.0206)
Sydney LD Dummy	0.0268*	0.0283***	0.0304*	0.0227	0.0357*
	(0.014)	(0.010)	(0.0076)	(0.014)	(0.0187)
Melbourne LD Dummy	0.0185	0.0162	0.0128	0.0202	0.0126
	(0.015)	(0.011)	(0.0101)	(0.014)	(0.018)
Constant	0.0966*	0.0587*	0.0036	0.0978*	0.1019*
	(0.01)	(0.032)	(0.0612)	(0.01)	(0.0202)
Observations	26	26	26	26	26
Instrumental Variable	No	No	Yes	No	Yes
R^2	0.963	0.967	0.9583	0.941	0.8626
Adjusted R^2	0.953	0.956	0.9452	0.911	0.7939

*Notes: robust standard errors in parentheses; $p < 0.1$ *, $p < 0.05$**, $p < 0.01$****
'LD': lockdown

The coefficients of column 3 control variables remain consistent with previous regression models and show a greater negative impact on credit transaction value as seen through the BNPL Sales coefficient. However, this suggested decrease in the dependent variable of roughly $13 million is insignificant as per a relatively significant p-value. The Debit Transactions and Sydney LD Dummy may be the driving forces of this regression model resulting in its high adjusted R^2 value of 0.9452. The coefficient of debit transactions is interpreted as roughly a $1 million increase in credit transactions for every $1 million transacted through debit. The Sydney LD Dummy highlights that credit experiences an increase in its proportion to total spending of around 3 percent. Similar results are shown in column 4 in terms of the Sydney LD Dummy, whereas debit is slightly more conservative in its positive impact. In column 5, coefficients of all variables remained consistent except for the primary test variable. The sign is positive but not significant, especially in comparison to column 3, the base model from Table 5, which suggests a highly significant negative impact of BNPL Customer increase on the dependent variable.

Overall, it seems clear that BNPL Customers worked to be a better operations indicator in terms of conservativeness and low variation of results throughout the regressions. The hypothesised notion that BNPL variables would negatively impact credit transactions has been shown through this analysis. Interestingly, debit cards positively influence credit transactions, but the opposite has been demonstrated during times since COVID emerged.

4.3 Bank-Level Results

The panel regression results testing the impact of BNPL sales on credit card levels as a fraction of total loans are laid out in Table 7[21]. As I use total loans as the denominator on the left-hand side, I do not double count this effect by adding the loans to deposit ratio on the right-hand side. Instead, I implement the log of total assets as my bank specific control.

This regression and all regressions in the bank-level analysis are robust to entity fixed effects and include clustered standard errors. Due to the construction of the dataset, time effects were not possible to add to the analysis. However, also due to data construction, there is an embedded time effect inherent in the control variables[22]. Furthermore, as the country results and data explored in Section 4.2 is comprised substantially of bank data, the time effect is inherent in that country-level analysis[23].

Column 1 depicts a baseline regression including only controls in which all coefficients are significant. The COVID dummy highlights a negative variable as is expected; however, the debit coefficient is positive, straying from the original hypothesis. The COVID dummy can be interpreted as causing an almost 2 percent decrease in the credit cards to loans ratio for every 1% increase in BNPL sales. The lockdown coefficients are both positive, likely conveying the online shopping surge which was present in Australia when restrictions were imposed. Both highlight a slight economic shift, less than a 1 percent decrease in the credit to loans dependent variable. Log of total assets conveys a negative coefficient consistently throughout the table, which is reasonable to expect since credit cards

[21] See Appendix Figure A.3 for histogram of residuals.
[22] As control variables are not dependent on banks, figures for each control are repeated for every entity for each quarter and are therefore "absorbed" when trying to add Time Effects to the panel regression. All left-hand side variables are adjusted for seasonality, reducing the need for time fixed effects. Additionally, much of these data have been adjusted for seasonality.
[23] The RBA Payments Statistics take into account all credit and debit transactions in Australia – bank data is therefore inherent within this.

and other loans are assets to banks. If total loans were to increase, this proportion of credit cards over total loans would decrease. This coefficient in all columns depicts a roughly 0.05 percent decrease in Credit Cards Loans/Total Loans.

TABLE 7: BANK LEVEL RESULTS WITH BNPL SALES AS MAIN TEST VARIABLE

Dependent Variable	Credit Card Loans/Total Loans				
	(1)	(2)	(3)	(4)	(5)
BNPL Sales		-2.1671	-0.6129	-1.4334	-2.4854
		(1.4754)	(1.6847)	(1.4016)	(2.9065)
BNPL Sales*Covid Dummy			-1.8538**		1.9827
			(0.8088)		(3.2573)
Debit*Covid Dummy				-0.1208***	-0.2213
				(0.0386)	(0.1689)
Covid Dummy	-0.0164***	-0.0131**	0.0076	0.0312**	0.046
	(0.0048)	(0.0052)	(0.0089)	(0.0141)	(0.0295)
Debit Transactions	0.066***	0.1687**	0.1082	0.1503*	0.1998
	(0.0248)	(0.0846)	(0.0883)	(0.0801)	(0.1512)
Sydney LD Dummy	0.0071***	0.0076***	0.0045*	0.003	0.0025
	(0.0024)	(0.0024)	(0.0023)	(0.002)	(0.002)
Melbourne LD Dummy	0.0063**	0.0053**	0.0016	0.0007	0.0008
	(0.0026)	(0.0024)	(0.0029)	(0.0027)	(0.0027)
Total Assets	-0.0497*	-0.0482*	-0.053**	-0.0541**	-0.0539**
	(0.0256)	(0.0255)	(0.0252)	(0.0258)	(0.0258)
Constant	0.7009**	0.6669**	0.7364**	0.7443**	0.7344**
	(0.3236)	(0.3178)	(0.3149)	(0.3221)	(0.3158)
Observations	130	130	130	130	130
Enitites	5	5	5	5	5
Entity Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2 Overall	0.817	0.802	0.848	0.857	0.856
Jarque-Bera	55.297	54.479	55.790	56.148	56.932

*Notes: clustered standard errors in parentheses; p < 0.1 *, p < 0.05**, p < 0.01****
'LD': lockdown

BNPL sales is added in column 2 and show a negative coefficient, in line with expectations but insignificant. Regardless, the coefficient signifies a 2% decrease in the dependent variable. The control variables remain consistent with column 1. In columns 3 and 4, I add the BNPL-Covid Interaction term and Debit-Covid interaction term, respectively, to witness their individual effect. Column 5 depicts their effect when placed together. In column 3, the BNPL and COVID interaction term is significant, suggesting an almost 2 percent decrease in the dependent variable at the time of the pandemic.

Column 4 represents the Debit and COVID interaction to be significant at the 1% level, informing that debit transactions in the presence of COVID negatively affect credit lending of banks.

This result is similar to that of the country level analysis Table 4, column 4, where individual debit and the debit interaction with COVID showed contrasting results. Specifically, debit cards may be linked to bank credit cards for repayment purposes and BNPL accounts alike. During COVID, it seems that debit transactions lowered bank credit loans as a fraction of total loans, suggesting that BNPL payments were taking precedence over credit card payments. Economically, the debit and COVID interaction term indicates that every 1 unit increase in BNPL Sales results in a 0.12 percent decrease in the credit cards to loans ratio. Column 4 retains a less significant but consistent take on the debit and COVID interaction but presents a positive but insignificant coefficient for the BNPL and COVID interaction. Based on the overall R^2 and Jarque-Bera of columns 4 and 5, both models are similarly explanatory. However, considering the lack of significance in the test variables in column 5, it seems as though column 4 is the most informative.

Moving forward, I run the same analysis using a different independent variable; BNPL Customers. These results are depicted in Table 8[24]. Column 2 shows the first addition of the independent variable of BNPL Customers. Column 2 highlights only the Sydney LD and Total Assets variable as significant. Moreover, the primary test variable conveys positive results throughout the analysis; however, they are insignificant and would have a minor economic impact on the credit to loans ratio. The high Jarque Bera results indicate that the models involved in this analysis do not answer the main research question. Column 3 represents the BNPL and COVID interaction as negatively impactful on the credit to total loans ratio; however, the coefficient is insignificant. Columns 4 and 5 report a significant debit and covid interaction coefficient, suggesting a roughly 0.1 percent decrease in credit cards as a fraction over total loans. Furthermore, the individual debit coefficient is significant and indicates a 0.04 percent *increase* in the credit cards to loans ratio, which is in line with the previous analysis using BNPL Sales. Overall, the results in this analysis can be assumed to be not as explanatory as the results in Table 7.

[24] See Appendix Figure A.4 for histogram of residuals.

TABLE 8: BANK LEVEL RESULTS WITH BNPL CUSTOMERS AS MAIN TEST VARIABLE

Dependent Variable	Credit Card Loans/Total Loans				
	(1)	(2)	(3)	(4)	(5)
BNPL Customers		0.0004	0.0006	0.0012	0.0011
		(0.0018)	(0.0019)	(0.0019)	(0.0019)
BNPL Customers*Covid Dummy			-0.0035		0.0019
			(0.009)		(0.011)
Debit*Covid Dummy				-0.0945*	-0.0986
				(0.0548)	(0.07)
Covid Dummy	-0.0164***	-0.0071	-0.0122	0.0277	0.032
	(0.0048)	(0.0054)	(0.0148)	(0.0212)	(0.0399)
Debit Transactions	0.066***	0.0209	0.0236	0.0421**	0.0416**
	(0.0248)	(0.0134)	(0.0159)	(0.0179)	(0.0177)
Sydney LD Dummy	0.0071***	0.0051*	0.004	0.0023	0.0027
	(0.0024)	(0.0029)	(0.004)	(0.0029)	(0.0035)
Melbourne LD Dummy	0.0063**	0.0041	0.0055	0.0003	-0.0006
	(0.0026)	(0.0034)	(0.0056)	(0.0047)	(0.0087)
Total Assets	-0.0497*	-0.0651**	-0.0656**	-0.0693***	-0.0692***
	(0.0256)	(0.0259)	(0.0259)	(0.0258)	(0.0259)
Constant	0.7009**	0.9086***	0.9152***	0.9579***	0.9566***
	(0.3236)	(0.33)	(0.3305)	(0.329)	(0.3306)
Observations	130	95	95	95	95
Enitites	5	5	5	5	5
Entity Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2 Overall	0.82	0.923	0.926	0.946	0.945
Jarque-Bera	55.30	1041.833	1051.469	1043.603	1041.490

*Notes: clustered standard errors in parentheses; p < 0.1 *, p < 0.05**, p < 0.01****
'LD': lockdown

As a sensitivity analysis on the bank-level results, I use an alternative dependent variable, credit card loans, as a fraction over total assets. Here, as I use total assets on the left-hand side as a denominator, I replace my left-hand side bank control with the loans to deposits ratio. The results of this analysis using BNPL Sales is shown below in Table 9[25].

Interestingly, in column 1, which comprises a control-only regression, the sign of debit transactions is flipped, suggesting a 1 percent decrease in credit loans to assets if debit transaction value increases by 1 percent. Considering the low significance of all the variables and substantially lower overall R^2 value of 0.21 compared to 0.81 when using credit cards to loans, it is likely that this

[25] See Appendix Figure A.5 for histograms of residuals.

model is not generating as informative results. Moving to column 2, the BNPL individual coefficient is negative, consistent with previous models. Still, it is not significant, which is a trait seen in all the controls of the model except Loans/Deposits. The Loans/Deposits ratio suggests a 0.3% increase in the credit to assets dependent variable. The Debit and Melbourne LD Dummy signs have also been flipped after adding the BNPL individual sales variable; however, it is difficult to pinpoint what is causing these changes with all variables being insignificant. Economically, the Melbourne LD Dummy would not have an impact regardless. It can be seen that there is a more significant negative load on BNPL Sales, and the Debit coefficient has risen to 0.3% from its previous negative state.

TABLE 9: BANK LEVEL RESULTS WITH BNPL SALES AND ALTERNATIVE DEPENDENT VARIABLE

Dependent Variable	Credit Card Loans/Total Assets				
	(1)	(2)	(3)	(4)	(5)
BNPL Sales		-6.935 (4.5583)	-8.4048* (4.9596)	-7.1379 (4.6784)	-12.558*** (4.435)
BNPL Sales*Covid Dummy			1.8011 (3.6574)		10.192 (8.8386)
Debit*Covid Dummy				0.0362 (0.2136)	-0.4809 (0.5308)
Covid Dummy	-0.0208 (0.0146)	-0.0101 (0.0168)	-0.0301 (0.0496)	-0.0234 (0.0844)	0.0529 (0.1115)
Debit Transactions	-0.0186 (0.0331)	0.3151 (0.2208)	0.3762 (0.2405)	0.3212 (0.2255)	0.5786*** (0.2177)
Sydney LD Dummy	0.0049 (0.0109)	0.0067 (0.0105)	0.0098 (0.0138)	0.0081 (0.0147)	0.0054 (0.0144)
Melbourne LD Dummy	0.0024 (0.0127)	-0.0006 (0.0133)	0.0032 (0.0169)	0.0009 (0.0171)	0.0014 (0.017)
Loans/Deposits	0.0365 (0.0235)	0.0376* (0.0225)	0.0381* (0.0226)	0.0377* (0.0227)	0.0394* (0.0224)
Constant	0.0178 (0.0342)	-0.0326 (0.0464)	-0.0418 (0.0479)	-0.0334 (0.0468)	-0.0734 (0.0463)
Observations	130	130	130	130	130
Enitites	5	5	5	5	5
Entity Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2 Overall	0.21	0.214	0.217	0.215	0.224
Jarque-Bera	66.56	62.477	64.724	63.305	62.741

*Notes: clustered standard errors in parentheses; p < 0.1 *, p < 0.05**, p < 0.01****
'LD': lockdown

Column 3 highlights a BNPL Sales coefficient as being negative and significant at the 10% level. The effect of BNPL sales has become more prominent, seeing an almost 9% decrease in the credit cards to loans ratio for every 1% increase in BNPL sales. Contrastingly, the BNPL-COVID interaction is positive – a considerable difference from previous models. It seems that where the negative load was weighted heavier in the BNPL-COVID interaction in previous results, with total assets as the denominator in the sensitivity analysis, credit as a fraction over such a variable is affected mainly at times where COVID did not exist.

Column 4 follows a similar trajectory to column 2 with no significant variables besides Loans/Deposits. However, signs are still in line with previous results using the original dependent variable – the individual debit coefficient is positive, lockdown dummies are positive, and loans to deposits is positive. However, the debit-COVID interaction dummy is showcasing a positive coefficient, contrasting to the original results. Once again, the lack of significance in all variables makes it unclear what is driving this change, especially when column 5 contradicts these results.

Column 5 contains both interaction terms – debit and BNPL, each with COVID. Although the interaction terms are insignificant, the BNPL-COVID term is positive, similar to in column 2, but the Debit-COVID term is negative. This suggests that since the emergence of COVID, BNPL sales and debit transactions have been accompanied by an increase and decrease in the proportion of credit card loans over total assets. Individually, debit transactions are positive and significant, aligning with previous results seen in the country and bank level analysis. The individual debit coefficient conveys a 0.5786 percentage increase in the proportion of credit cards to loans for every 1 unit increase in debit transactions as a fraction of total spending. Additionally, the individual BNPL term is highly significant at the 1% level, implying a 13 percent decrease in credit cards as a share of total assets. This conveys the overall decline in the ratio of credit cards over total assets is affected by individual BNPL sales more than COVID related terms.

In general, however, the results are insignificant. It is clear that some coefficients are uniform with previous results and those that are inconsistent are also insignificant. The sensitivity analysis highlights that perhaps credit cards taken over total assets does not convey the most useful information.

Continuing forward, I run the same analysis using BNPL Customers as the independent variable. These results are laid out in Table 10[26]. Unlike when testing BNPL sales as the independent variable, BNPL customers highlights a positive but insignificant coefficient in column 1. The COVID dummy is significant at the 10% level, suggesting a 2 percent increase in credit cards as a fraction over total assets when COVID is present. The bank-specific variable, loans to deposits, is highly significant across

[26] See Appendix Figure A.6 for histograms of residuals.

all models, excluding the control-only model, suggesting an average 0.3% decrease in the dependent variable.

TABLE 10: BANK LEVEL RESULTS WITH BNPL CUSTOMERS AND ALTERNATIVE DEPENDENT VARIABLE

Dependent Variable	Credit Card Loans/Total Assets				
	(1)	(2)	(3)	(4)	(5)
BNPL Customers		0.003 (0.0055)	0.0016 (0.0059)	-0.0005 (0.0057)	-0.0003 (0.006)
BNPL Customers*Covid Dummy			0.0164 (0.0196)		-0.0025 (0.024)
Debit*Covid Dummy				0.3312** (0.1299)	0.337** (0.1677)
Covid Dummy	-0.0208 (0.0146)	0.028* (0.0147)	0.0519 (0.0341)	-0.0917* (0.0502)	-0.0974 (0.0935)
Debit Transactions	-0.0186 (0.0331)	-0.0568 (0.0403)	-0.0674 (0.0447)	-0.1177** (0.0447)	-0.1171** (0.045)
Sydney LD Dummy	0.0049 (0.0109)	-0.0111 (0.0089)	-0.0064 (0.0105)	-0.0019 (0.0096)	-0.0025 (0.0095)
Melbourne LD Dummy	0.0024 (0.0127)	-0.0117 (0.0101)	-0.0182 (0.0143)	0.0018 (0.0121)	0.0031 (0.0207)
Loans/Deposits	0.0365 (0.0235)	0.2832*** (0.0356)	0.2844*** (0.0359)	0.2978*** (0.0382)	0.2978*** (0.0384)
Constant	0.0178 (0.0342)	-0.3043*** (0.0475)	-0.3046*** (0.0474)	-0.3136*** (0.0488)	-0.3137*** (0.049)
Observations	130	95	95	95	95
Enitites	5	5	5	5	5
Entity Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2 Overall	0.21	0.826	0.828	0.848	0.848
Jarque-Bera	66.56	35.710	37.647	58.994	59.700

*Notes: clustered standard errors in parentheses; p < 0.1 *, p < 0.05**, p < 0.01****
'LD': lockdown

Column 3 also highlights a small and insignificant impact of BNPL customers on the credit card to assets ratio. This is apparent across all models, even when it is negative in columns 4 and 5. It is indeed columns 4 and 5 that are the most informative in this analysis. It can be seen that there is a shift in the sign of the debit-COVID interaction terms, perhaps highlighting that debit payments helped to increase the credit loans to assets ratio. Debit individually conveys a negative coefficient that is inconsistent with previous models, and the covid dummy also provided negative results. In column 5, with the inclusion of both COVID interaction terms together, it seemed that the positive Debit-Covid interaction caused the BNPL-Covid interaction to flip signs. This suggests that the positive effect is weighed more in the debit-COVID interaction term.

Overall, some coefficients, particularly that of the COVID interaction terms, are inconsistent with previous models. The hypothesis that BNPL negatively affects credit card transactions at a bank level can be seen through the bank analysis with some varying results. However, significant coefficients aligned with expectations. Debit cards followed a similar pattern to the country analysis, usually positive at an individual capacity and negative when interacting with the COVID Dummy. There was some variation in the Debit coefficient when using the alternative dependent variable, credit loans over total assets, with significant values shown while testing BNPL Customers. Essentially, Debit decreases the ratio of credit cards to total assets before COVID emerged and had the opposite effect after COVID emerged. Perhaps, this suggests that debit cards became a larger factor in bank assets in comparison to credit cards.

4.4 E-Commerce Case Study: Afterpay

As an extension of the main results, I isolate the E-commerce transactions which make up a part of the credit and debit transactions used in the original country-level analysis. I believe that, based on the results in prior tables regarding BNPL variables and their interaction with COVID, there may be some extra information present in E-commerce data. It stands to reason that since the pandemic began and cities were forced into lockdown, particularly Sydney and Melbourne, online retail has become volatile (ABS 2021). The ABS even reports that it is likely that online retail figures were under-reported before, seen through the instability inherent in the sudden change.

It is important to acknowledge that the regression in Table 11 only accounts for Afterpay sales figures from 2018 to 2021 as percentage contributions of online sales was only available for these years[27]. These figures are then placed as a fraction over the total online retail turnover reported monthly on the ABS website (ABS 2021). I have summed these data at a quarterly frequency from 2018 to 2021. However, assumptions can be made based on the homogeneity of companies in the BNPL sector: this analysis is a general conceptualisation of the online BNPL market.

To accomplish the task of drawing connections between Afterpay, 'Device not present' transactions are available in the RBA payments statistics at a monthly frequency which I have collated at a quarterly level using summation[28]. 'Device not present' transactions accumulate all purchases

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[27] Percentage of online sales contribution was found by searching all annual and half-yearly reports. I then calculated the online sales portion of Afterpay sales only. These data were then adjusted for seasonality based on Hood 2017. See appendix Figure A.8.
[28] See appendix Figure A.7 for time series visual of credit and debit 'Device not present' transactions values.

made through a virtual payment portal like a merchant website in which you must enter your card (debit or credit) details to make a purchase. As the dependent variable, I use the ‘Device not present’ credit transactions as a ratio to the total value of credit transactions used in the country level analysis. Similarly, the debit transactions figure is the ‘Device not present’ debit transactions as a ratio to the total value of debit transactions. I remove Credit Limit from this analysis as it is the total of all credit card limits and is too broad to use in this analysis. The binary variables remain the same, and interaction terms are still used. The results are displayed in Table 11.

The control specific regression in column 1 highlights a significant and negative coefficient of the COVID dummy, remaining consistent in all columns besides 4 and 5, where it seems the debit-COVID interaction has taken on more of this negative load. This is uniform with Tables 4 & 5 and 7 & 8 in the country and bank analysis, respectively. Another fundamental similarity is the fact that debit transactions individually remain positive causing an average increase of 2.94% in E-Commerce credit transactions across the columns. It is useful to note that, while the BNPL coefficient in columns 2 until 4 are not significant, they retain the negative sign that aligns with the central hypothesis. This highlights further that BNPLs have had a negative impact on the E-commerce credit sector. Column 4 presents a negative Debit coefficient significant at the 5% level, suggesting an almost 2% drop in credit card E-commerce payments since COVID was introduced. In column 5, however, the APT-COVID interaction is positive, while the Debit-COVID interaction has a greater negative impact at 3%. This conveys consumers were using debit cards more and BNPL less during COVID in the E-commerce market. The adjusted R^2 and Jarque Bera statistics of the regressions in Table 11 are consistently reasonable. An average adjusted R^2 of 0.78 and Jarque-Bera of 0.622 across the columns provides further evidence of the substantial explanatory nature of the results.

Furthermore, it can be seen that the Sydney lockdown coefficient is positive, suggesting higher sales over online shopping during times in which Sydney was under heavy restrictions. Similarly, the Melbourne lockdown coefficient is positive and significant in all columns but columns 4 and 5. In column 5, it is negative, with the addition of both COVID interactions together. This could be the outcome of consumers in Melbourne using their debit cards over their credit cards or being more likely to use debit cards when purchasing online.

The hypothesis that online BNPL sales would negatively impact credit transactions has been shown through my E-commerce case study. Spending from home became high in a period of increased tension, and this is shown in the results.

TABLE 11: E-COMMERCE CASE STUDY RESULTS

Dependent Variable	E-commerce Credit/Total Credit Transactions				
	(1)	(2)	(3)	(4)	(5)
APT Sales		-0.1664 (0.296)	-0.1177 (0.323)	-0.1169 (0.308)	-0.1391 (0.333)
APT Sales*Covid Dummy			-0.2588 (0.237)		0.3544 (0.365)
Debit*Covid Dummy				-1.6672** (0.838)	-3.1666* (1.035)
Covid Dummy	-0.0654* (0.011)	-0.105* (0.026)	-0.0514 (0.066)	0.2766 (0.206)	0.5464* (0.16)
Debit Transactions	2.201* (0.104)	3.1703* (0.735)	3.0954* (0.75)	3.1146* (0.723)	3.1669* (0.781)
Sydney LD Dummy	0.0066 (0.007)	0.0082 (0.009)	0.0116** (0.006)	0.0093** (0.005)	0.0055* (0.003)
Melbourne LD Dummy	0.0318* (0.007)	0.0492** (0.021)	0.0558* (0.016)	0.0271 (0.027)	-0.0017 (0.013)
Constant	-0.0074 (0.016)	-0.1558* (0.092)	-0.1507* (0.091)	-0.1544* (0.088)	-0.1601* (0.094)
Observations	26	16	16	16	16
Cov. Estimator	Robust	Robust	Robust	Robust	Robust
Adjusted R^2	0.93	0.766	0.747	0.754	0.726
Jarque-Bera	0.352	0.658	0.61	0.693	0.797

*Notes: robust standard errors in parentheses; p < 0.1 *, p < 0.05**, p < 0.01****
'LD': lockdown

4.5 Limitations

The frequency at which BNPL data, particularly sales, customer numbers, merchant numbers, and revenue, is available is quarterly at its most granular level. Companies, mostly following their inception, will tend to publish more frequent statistics, sometimes even monthly or quarterly, in order to show some form of comparison. This allows the company to highlight improvement or decline. As companies expand and enter the growth and maturity cycle of their life, the data becomes less granular. Additionally, BNPL companies were only introduced in the past six to seven years. Therefore, even acquiring quarterly data for such an area may not provide as accurate a result as longer time series could.

Furthermore, the possibility of expanding this research overseas was not possible due to the unavailability of particular databases such as BankScope, which could have afforded me the balance sheet items of overseas banks. Australian bank data was available monthly from 2002 to 2021, but I could not find a similar foreign dataset elsewhere.

Using programming software that was unable to automatically account for time effects is another important limitation in the bank level analysis. Fortunately, the country level analysis considers time and is majorly comprised of bank data.

4.6 Implications for Future Research

There is a crucial discussion occurring between BNPL companies and policymakers regarding the ‘no surcharge’ rule, which I have elaborated on in the literature review section of this thesis. Merchants take on BNPL fees as it provides them with greater volumes of sales. However, policymakers are suggesting this burden be placed on the customer as well – this may cause a significant drop in the BNPL consumer base as minimal to non-existent fees are one of their main selling points from a marketing perspective. Data is available in the RBA payments statistics section of the RBA website surrounding merchant fees of various credit card companies like VISA, Mastercard, American Express and others. A future study may use such data and hypothesise that banks, such as CBA and NAB, creating their own BNPL products with lower merchant fees may rally against original BNPLs. Suppose these bank-related products are easily accessible and improve user interfaces that attract individuals to existing BNPLs like Afterpay and Zippay. In that case, it is possible that not only young people will gravitate towards trusted bank-related products, but older individuals will engage in using such a facility they may not have considered otherwise. Thus, causing an interesting dynamic between BNPLs and bank ‘pay later’ options.

An important area of research that branches slightly out of the finance sector would be analysing consumer perception of BNPL and credit. While the RBA and ASIC have provided extensive information through consumer surveys, conducting more specific research with random individuals would be interesting. Consumer perception was something I was not able to gather primary data on for this research. In recognising the importance of consumers, another avenue one could take in this research area is to investigate the impact of geographical location, as seen in Jagtiani and Lemieux (2018). Furthermore, distance to banks and availability of internet connections could be perused to expand on the ‘why’ of BNPL usage.

Finally, a cross-country analysis of the effects of BNPL would be beneficial. I was unable to do so due to data constraints, but if individuals or researchers abroad have access to such data, it would be interesting to see the development and effect of BNPL throughout the world. BNPLs themselves tend to separate their key figures by global regions, often collating Australia with New Zealand and countries in Asia.

5. Conclusion

When the RBA and ASIC began their perusal of BNPL services as an industry instead of as an extension of fintechs, it was clear that the sector was taking on a shape and form greater than anticipated. Through the development of this thesis, I reviewed current news and relevant literature that suggested a plethora of reasons to investigate this industry. Most credit card users were seen to be older individuals. In contrast, younger people in the millennial and Generation z category were hesitant to use credit cards due to risk, poor credit scores and low income. While consumer protection issues are inherent within the BNPL sector, namely financial illiteracy, over-commitment, and a nonchalant perception of late fees, regulators like ASIC are working to ensure better consumer outcomes. However, there is an additional policymaker concern regarding the no-surcharge rule. The eradication of this BNPL imposed rule by the RBA would be a key factor in possibly slowing down the booming BNPL industry. Customers may be unwilling to take on the costs that originally burdened merchants only.

Since the large scale introduction of BNPL products in the market in 2015, it was clear that credit card usage plateaued and then began its descent. While this could likely be the result of many economic changes, it is clear that BNPL growth and its stimulation through seemingly risk-averse consumers is a key trigger. There was a need to quantify the extent to which BNPLs played a part in this considerable economic switch. Therefore, this research aimed to uncover the effects of BNPL operations, specifically sales and customers, on the credit lending system of Australia. Through the discoveries made in this thesis, I begin an empirical discussion on a prevalent sector of the Australian market and its impact on credit lending at both a country and bank level. I conduct a time series and panel regression for country level and bank level data, respectively, with data ranging from 2015 to 2021. I find that BNPLs have a negative effect on Australian credit card transaction value. To further realise this effect, I use an instrumental variable in a TSLS regression to find that the coefficients hold in terms of signs and significance and generally show a larger negative effect. Furthermore, this effect still holds at the bank level as I regress BNPL variables on the bank credit cards to loans ratio. Additionally, when using the alternative dependent variable, credit cards to assets ratio, the majority of the bank level results retain a similar coefficient with differences shown mostly in debit transactions.

Throughout the hypothesis development, I recognised connections between debit, credit and BNPLs. The results show that BNPLs sales negatively affect credit lending in Australia and are mostly significant both statistically and economically. BNPL unique customers do have a negative effect which is economically significant at the country level. It is important to note that these effects are interdependent on the COVID-19 pandemic. The addition of interacting BNPL and Debit Transactions with COVID has shown a greater negative effect since the emergence of the disease. The effect of BNPL sales at times since COVID is significantly more negative than that of BNPL sales alone. A slightly similar relation is seen with the Debit-COVID interaction, which introduces a contrast between consistently positive individual debit coefficients versus its steadily negative interaction with COVID except when regressing with an alternative dependent variable. This can be justified by the volatility of spending habits and the striving retail sector. From an industry perspective, fashion retailing fell by 15.7%, hospitality by 7% and department stores by 10.2% (ABS 2021). These declines were only exacerbated as consumers discontinued physical shopping. Food retailing has seen the largest rise at only 2.1%, as restrictions limit mobility and place households under lockdown. The only other retail rise of 0.8% was seen through online shopping, which was the basis of conducting a E-commerce focused time series regression analysis. I used RBA E-commerce data and took Afterpay online sales from 2018 to 2021 to discover that online shopping via Afterpay negatively affects online purchases made using credit cards.

Further implications and contributions of this study stem from it being the first empirical study that aims to draw conclusions on how BNPL services affect credit lending. With that in mind, this thesis is a gateway for other countries to determine the possible impact of these innovative fintechs making space in their market. Furthermore, by drawing connections between the homogeneity of consumer and demographic shifts, countries can claim a similar result of BNPL focused spending in their economy. Additionally, this thesis can be utilised by BNPL firms and banks alike. BNPL firms can revisit their business model and determine whether more focus should be placed on sales or customers based on the results. Banks will have evidence of the shifting consumer focus and can plan differently for the future based on the demand for certain types of products.

Nonetheless, adopting a forward-looking perspective on the future of the BNPL industry, I believe that it will grow exponentially through the passage of time. Within the next two decades, credit card usage could decline further, aided by older generations moving towards retirement while younger generations utilise more accessible payment solutions through BNPL services.

Appendix

TABLE A.1: VARIABLE DESCRIPTIONS

Variable	Definition	Source
Credit Card Transactions	Total value of credit card transactions from Australian credit cards	RBA Payments Statistics
Loans to Households: Credit Cards	Balance sheet item of personal credit cards liabilities issued to households from banks	APRA Monthly ADI Statistics
BNPL Sales	Gross sales accumulated by 4 BNPL fintech companies	Company annual, semi-annual, and monthly reports via ASX website
BNPL Customers	Unique customers added by 4 BNPL fintech companies	Company annual, semi-annual, and monthly reports via ASX website
Debit Card Transactions	Total value of debit card transactions from Australian credit cards	RBA Payments Statistics
Credit Limit	Total credit card limit of Australian credit cards	RBA Payments Statistics
Loans/Deposits	Total loans and advances of banks ratio to total deposits of banks	APRA Monthly ADI Statistics
Total Assets	Total resident assets of banks	APRA Monthly ADI Statistics
COVID	Binary variable for when COVID emerged in the world	World Health Organisation
Sydney Lockdown	Binary variable for times when Sydney was under heavy restrictions/lockdowns	Parliament of Australia NSW Health
Melbourne Lockdown	Binary variable for times when Melbourne was under heavy restrictions/lockdowns	Parliament of Australia NSW Health
Trends (instrument)	Average Google mentions of 4 key BNPL fintech companies	Google Trends
APT Sales	Online sales of Afterpay	Company annual, semi-annual, and monthly reports via ASX website
E-commerce credit	‘Device not present’ credit transactions	RBA Payments Statistics
E-commerce debit	‘Device not present’ debit transactions	RBA Payments Statistics

TABLE A.2: ABBREVIATIONS

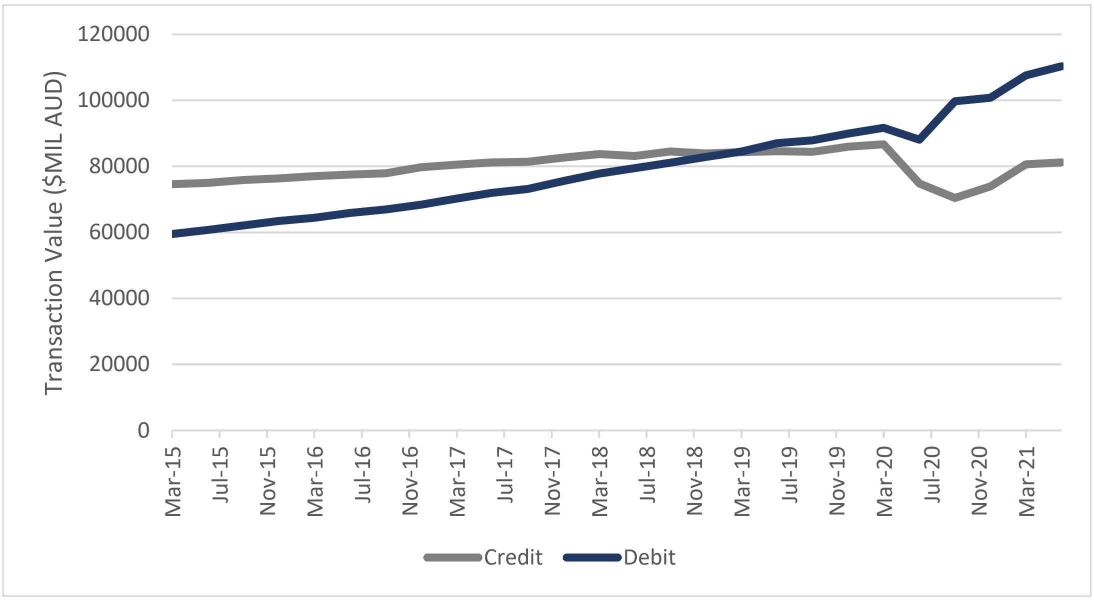
Abbreviation	Definition
ABS	Australian Bureau of Statistics
ADF	Augmented Dickey-Fuller Test
ADI	Authorised Deposit-Taking Institution
ANZ	Australia and New Zealand Bank
APRA	Australian Prudential Regulatory Authority
APT	Afterpay Inc
ASIC	Australian Securities and Investment Commission
ASX	Australian Securities Exchange
AUD	Australian Dollar
BNPL	Buy Now, Pay Later
CBA	Commonwealth Bank of Australia
CFO	Chief Financial Officer
COVID	Corona Virus Disease
CPL	Citigroup Pty Ltd
CPS	Consumer Payments Survey
GFC	Global Financial Crisis
KPSS	Kwiatkowski–Phillips–Schmidt–Shin Test
LD	Lockdown
NAB	National Australia Bank
NPP	New Payments Platform
NSW	New South Wales
NZ	New Zealand
NZD	New Zealand Dollars
OLS	Ordinary Least Squares
OVB	Omitted Variables Bias
R^2	R squared
RBA	Reserve Bank of Australia
SEM	Single Economic Market
TSLS	Two Staged Least Squares
UBS	United Bank of Switzerland
USD	United States Dollars
WBC	Westpac Banking Corporation
WHO	World Health Organisation

TABLE A.3: DESCRIPTIVE STATISTICS PRE-SCALING/TRANSFORMATION

Variable	Obs.	Mean	Std	Min	Max
Loans to Households: Credit Cards**	130	7284.18	2458.28	3533.10	11673.40
Total Value of Credit Transactions	26	80073.38	4339.84	70420.72	86689.96
BNPL Sales	26	1258.90	1269.03	-110.45	3711.34
BNPL Customers	19	0.48	0.24	0.17	1.04
Total Value of Debit Transactions	26	79655.00	14565.10	59500.54	110336.74
Total Assets**	130	592011.90	305302.90	14357.10	1021082.00
Credit Limit	26	134975.77	6670.04	119244.44	141634.03

Notes: Table A.3 displays the descriptive statistics for all original variables before scaling/transformation between 2015 and 2021. Loans to Households: Credit Cards is the credit card loans issued by banks in millions of dollars. Total Value of Credit Transactions is the total value of Australian credit transactions in millions of dollars. BNPL Sales is the collective sales of 4 BNPL companies in millions of dollars. BNPL Cus is the BNPL unique customer numbers of 4 BNPL companies in millions. Total Value of Debit Transactions is the total value of debit transactions in millions of dollars. Total Assets is the total resident assets of banks. Credit Limit is the credit limits for Australian credit cards. ***bank-specific variables*

FIGURE A.1: SEASONALLY ADJUSTED SERIES OF CREDIT AND DEBIT TRANSACTIONS



Notes: Figure A.1 shows the shift of credit and debit. Debit seems to have overpowered credit in 2019.

The time series regression results generated for the initial country level analysis are displayed in Table A.4. Columns 1, 2 and 3 excluded an important variable, debit transactions, which caused the results, specifically in column 2 to be underwhelming based on previous literature and current market conditions. Debit cards were excluded originally to understand its effect considering its competitive nature with BNPL. Column 2 highlighted a *positive* and *significant* BNPL Sales coefficient as well as a negative COVID Dummy, inconsistent with column 1. In column 3, BNPL Customers still agreed with the original hypothesis, highlighting a slightly significant coefficient, but the COVID factors remained inconsistent with columns 1 and 2.

TABLE A.4: COUNTRY LEVEL ANALYSIS EXCLUDING DEBIT CARDS

Dependent Variable	Total Credit Card Transaction Value					
	(1)	(2)	(3)	(4)	(5)	(6)
BNPL Sales		9.7639***			-5.4273	
		(1.090)			(3.839)	
BNPL Customers			-0.0161			-0.0076
			(0.008)*			(0.004)**
Debit Transactions				0.5676	0.8270***	0.5401
				(0.055)*	(0.209)	(0.058)*
Credit Limit	-0.0307	-0.0095	-0.0251	-0.005	-0.0051	-0.0047
	(0.004)*	(0.002)	(0.006)*	(0.003)*	(0.004)	(0.003)
Covid Dummy	0.013	-0.0561***	0.008	-0.0528	-0.0444***	-0.053
	(0.018)	(0.024)	(0.017)	(0.015)*	(0.014)	(0.015)*
Sydney LD Dummy	0.0273	0.0243	0.0164	0.0268	0.0283***	0.0227
	(0.017)	(0.021)	(0.016)	(0.014)*	(0.010)	(0.014)
Melbourne LD Dummy	-0.0048	0.0186	0.0008	0.0185	0.0162	0.0202
	(0.017)	(0.021)	(0.015)	(0.015)	(0.011)	(0.014)
Constant	0.2019	0.1835***	0.1963	0.0966	0.0587*	0.0978
	(0.003)*	(0.002)	(0.007)*	(0.01)*	(0.032)	(0.01)*
Observations	26	26	26	26	26	26
R^2	0.825	0.931	0.745	0.963	0.967	0.941
Adjusted R^2	0.791	0.914	0.647	0.953	0.956	0.911
Jarque-Bera	0.812	2.096	0.965	1.806	3.697	0.085
Condition No.	Low	Low	Low	Low	High	Low

*Notes: robust standard errors in parentheses; p < 0.1 *, p < 0.05**, p < 0.01****
'LD': lockdown

Column 4, however, is where I have added the Debit Transactions Value as a fraction over total spending in the baseline controls regression. Following this addition, columns 5 and 6, including BNPL Sales and BNPL Customers, respectively, contain consistent coefficients among all variables. Column

5 is where a significant adjustment occurs compared to column 2. As expected, debit card transactions alter results, specifically the main test variable. The sign for BNPL sales is now negative, proving a need for further investigation as the debit card coefficient is highly explanatory, showcasing an extremely low p-value. Considering the change from a *positive* to *negative* BNPL sales coefficient with the inclusion of debit card transactions and the hypothesis of BNPL sales having a negative coefficient, I look to the omitted variable bias (OVB) analysis.

TABLE A.5: PEARSONS CORRELATION COEFFICIENT FOR OVB 1

	Debit Card Transaction Value
BNPL Sales	0.9915***
Credit Card Transaction Value	0.9548***

*Notes: p < 0.1 *, p < 0.05**, p < 0.01****

Table A.5 shows the Pearson's correlation coefficients between Debit Card Transactions and the test variable, as well as Debit Card Transactions and the dependent variable. The positive and significant coefficients highlight that there is indeed an *upward bias* inherent in the BNPL Sales coefficient when Debit Transactions are *not* included in the regression model.

TABLE A.6: REGRESSION OF TOTAL CREDIT CARD TRANSACTIONS WITH ALTERNATIVE TOTAL SPEND PROXY

Dependent Variable	Total Credit Card Transaction Value					
	(1)	(2)	(3)	(4)	(5)	(6)
BNPL Sales		9.9086***	11.2269***		-9.3438***	-9.2644***
		(2.587)	(1.747)		(1.543)	(1.433)
Debit Transactions				0.7426***	1.1039***	1.1051***
				(0.099)	(0.081)	(0.075)
Credit Limit	-0.0025***	-0.0004		0.0005	-3.258e-05	
	(0.000)	(0.0004)		(0.001)	(0.000)	
Covid Dummy	-0.0063**	-0.0099***	-0.0100***	-0.0071***	-0.0041***	-0.0041***
	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
Sydney LD Dummy	0.0041*	0.003	0.0027	0.0022*	0.0023***	0.0023***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Melbourne LD Dummy	0.0014	0.0026	0.0028	0.0022*	0.0015**	0.0015*
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Constant	0.0209***	0.0191***	0.0188***	0.0066***	0.0015	0.0015
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)
Observations	26	26	26	26	26	26
R^2	0.458	0.627	0.622	0.894	0.944	0.944
Adjusted R^2	0.355	0.533	0.55	0.867	0.926	0.93
Jarque-Bera	4.534	3.367	3.02	0.306	2.181	2.505
Condition No.	Low	High	High	Low	High	High

*Notes: standard errors clustered by banks in parentheses; p < 0.1 *, p < 0.05**, p < 0.01****
'LD': lockdown

The regression in Table A.6 is run with Credit Transactions, BNPL Sales and Debit Transactions placed over the denominator: total spending. However, total spending has two additional variables in its sum. Total spending is made up of BNPL Sales, Credit Transaction Value, Debit Transaction Value, **Direct Payments** and **New Payments Platform (NPP)**. This analysis was added to check whether the results hold with a larger denominator encompassing other types of payments. As is apparent, the results hold with a minor difference of a positive coefficient for the Melbourne LD Dummy (1) and credit limit being slightly inconsistent in column 4. Column 4, however, is where I have added the Debit Transactions Value as a fraction over total spending. A small change is highlighted in the coefficient of Credit Limit having flipped signs; however, this value is extremely small, as seen in columns 1 and 2, while retaining no significance. Additionally, it does not have a strong economic impact as a percentage point increase in credit limit causes a 0.0005 percentage point increase in credit transaction values. Due to the altered coefficients when adding Debit Transactions, I once again look to the OVB.

TABLE A.7: PEARSONS CORRELATION COEFFICIENT FOR OVB 2

	Debit Card Transaction Value
BNPL Sales	0.9336***
Credit Card Transaction Value	0.7153***

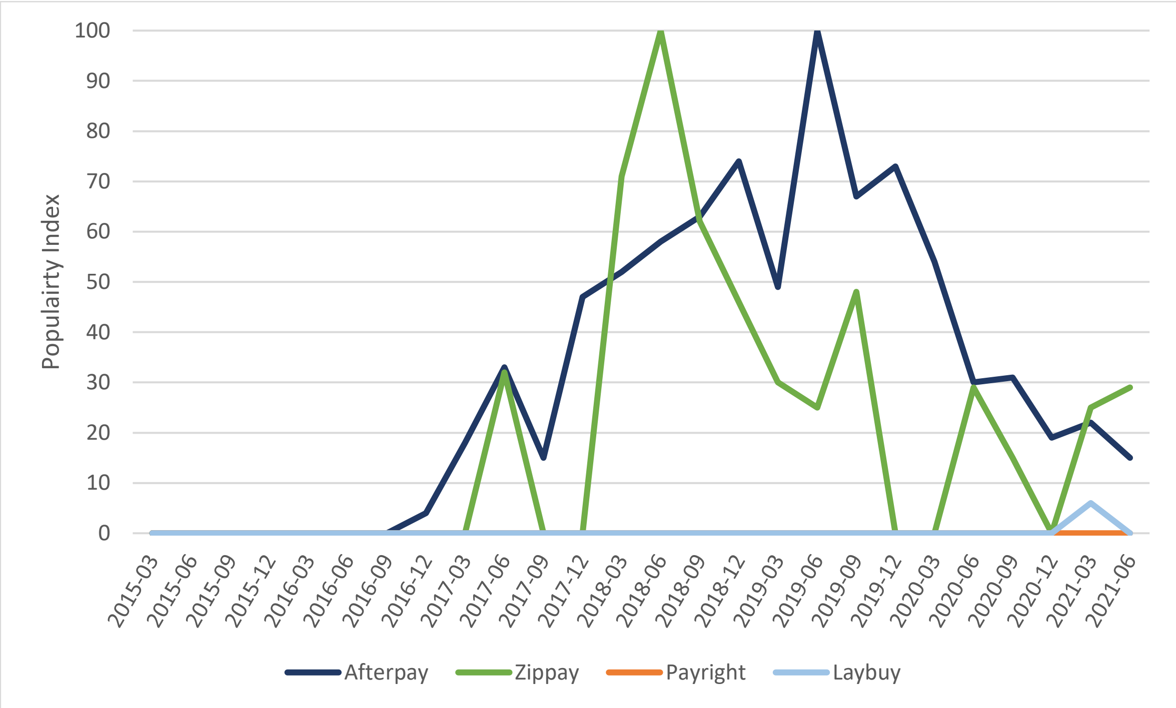
*Notes: $p < 0.1$ *, $p < 0.05$**, $p < 0.01$****

The correlation coefficients here show similar results to the main regression correlations. This brings the focus to column 6 in Table A.6, where I have excluded credit limit due to its insignificance. This decision is supported by the minimal changes in all coefficients of column 6 when credit limit is excluded. This column includes a high R^2 of 0.944, a low Jarque-Bera of 2.505. As hypothesised, the BNPL coefficient is negative, highlighting that a 1 unit increase in BNPL Sales causes a $9.26 million decrease in credit card transaction values[29]. This satisfactory result conveys the nature of BNPL rising and the inverse decrease seen in Australian credit lending overall. It is important to note that the reason for not expanding the main results using this broader 'total spending' term is due to the fact that BNPL services are largely used for retail purposes, with most BNPLs not yet available in the food industry. Therefore, as it is wiser to sum like with like, I have excluded the payment methods for which BNPLs cannot be substituted. Direct Payments and NPP were removed from the main regression as these types of payments are not substitutes for BNPL. In the main regression, Total Spending (BNPL

[29] As both Credit Card Transaction Value and BNPL Sales are placed as a fraction over the same variable, Total Spend, this interpretation is satisfactory.

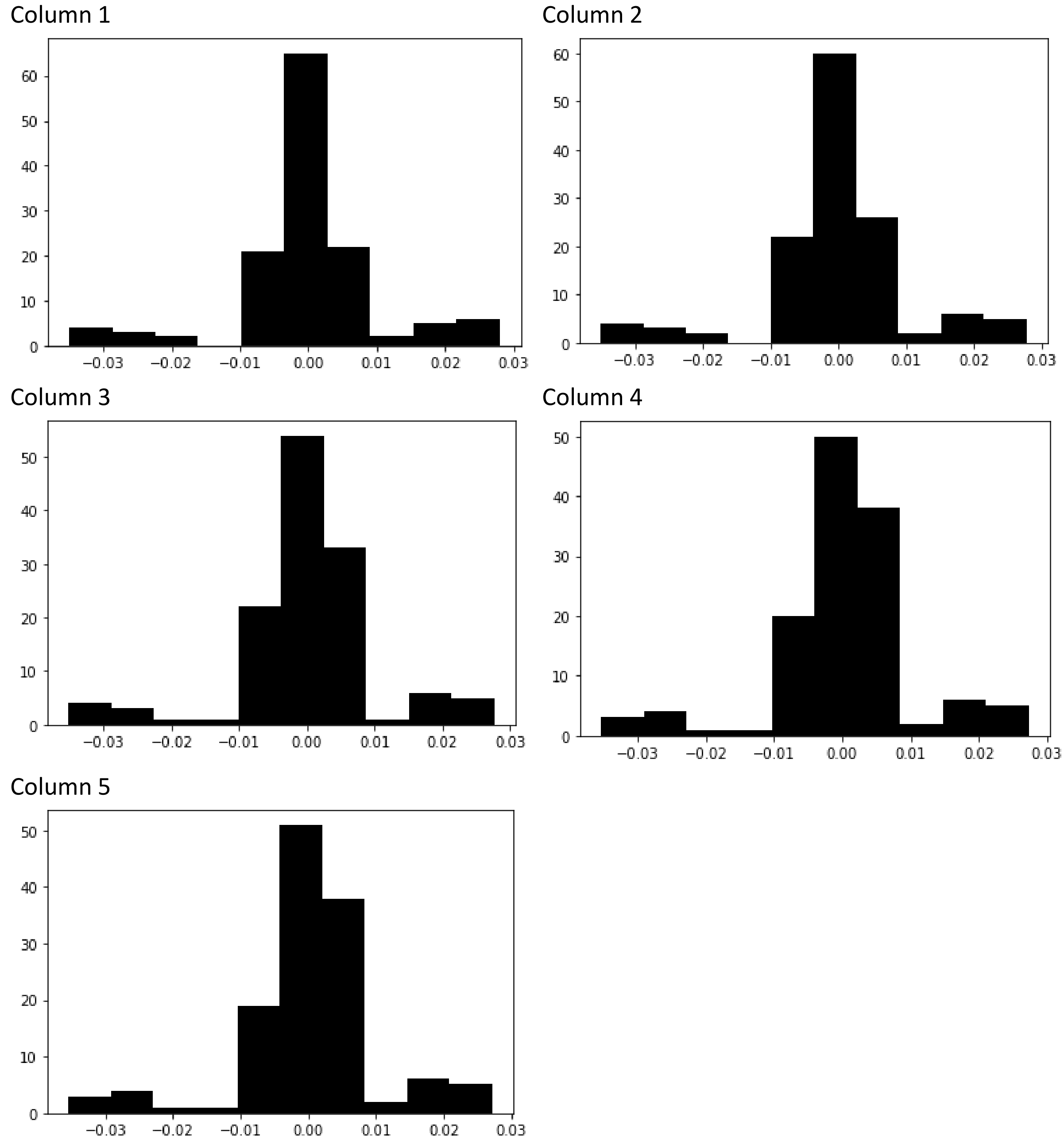
Sales + Credit Transactions + Debit Transactions + Cheque) worked well as each item involved in the denominator is a substitute for the other.

FIGURE A.2: INSTRUMENTAL VARIABLE 'GOOGLE TRENDS' DATA BNPL COMPANIES



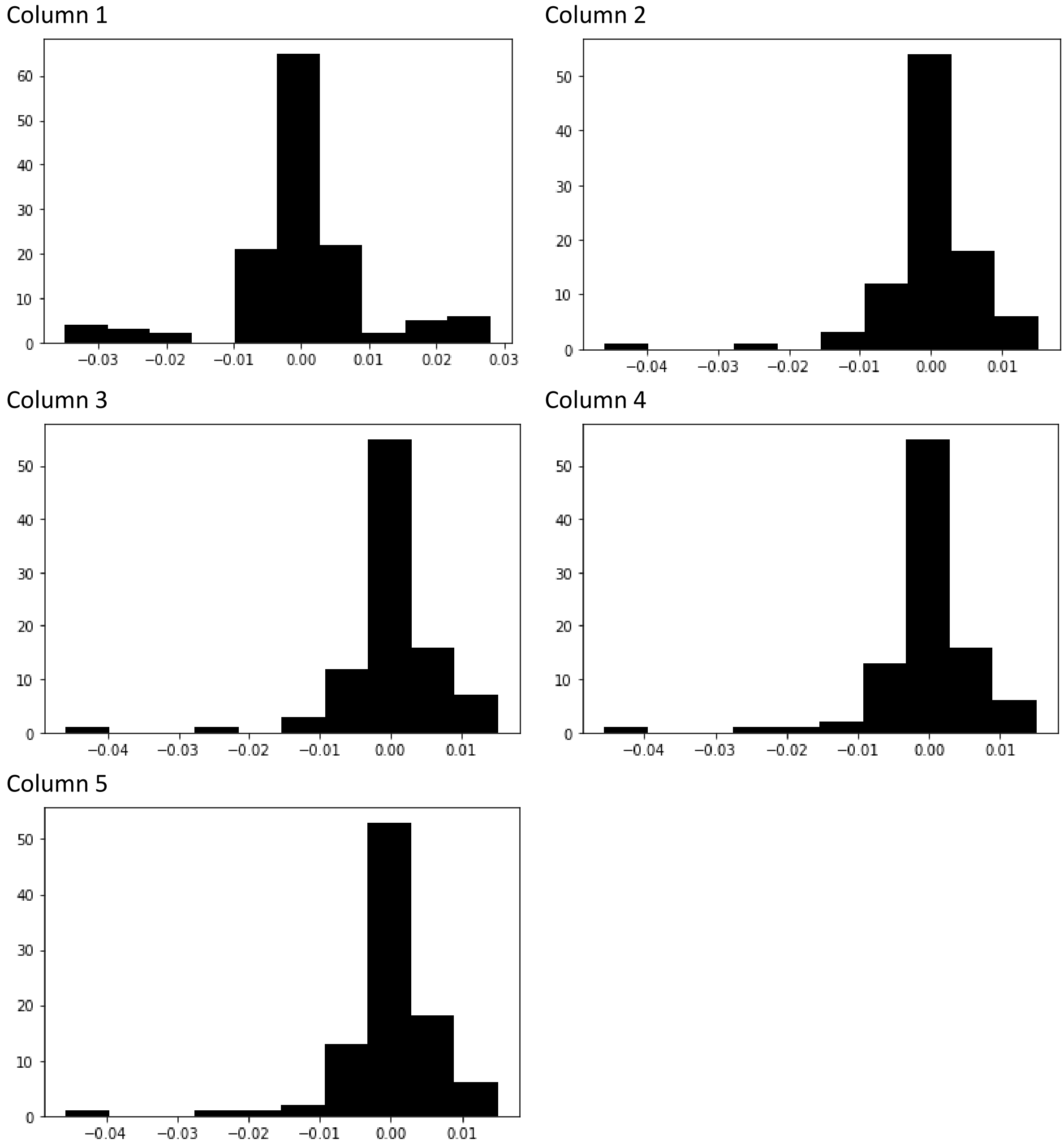
Notes: Figure A.2 shows Afterpay and Zippay are similar in terms of their popularity trajectory, with Payright and Laybuy essentially having no mention even in recent years.

FIGURE A.3: HISTOGRAMS OF RESIDUALS FOR PANEL ANALYSIS IN TABLE 7



Notes: Figure A.3 shows the histograms of residuals for each column in the bank-level panel analysis testing the effect of BNPL Sales on credit cards as a fraction of total loans.

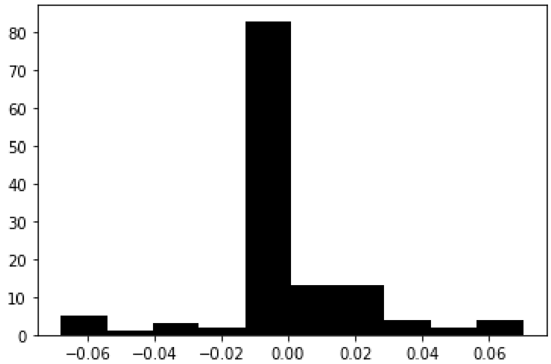
FIGURE A.4: HISTOGRAMS OF RESIDUALS FOR PANEL ANALYSIS IN TABLE 8



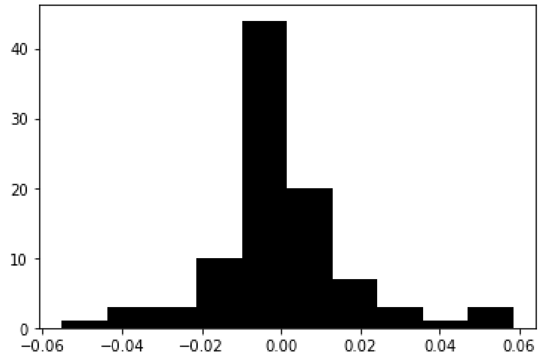
Notes: Figure A.4 shows the histograms of residuals for each column in the bank-level panel analysis testing the effect of BNPL Customers on credit cards as a fraction of total loans.

FIGURE A.5: HISTOGRAMS OF RESIDUALS FOR PANEL ANALYSIS IN TABLE 9

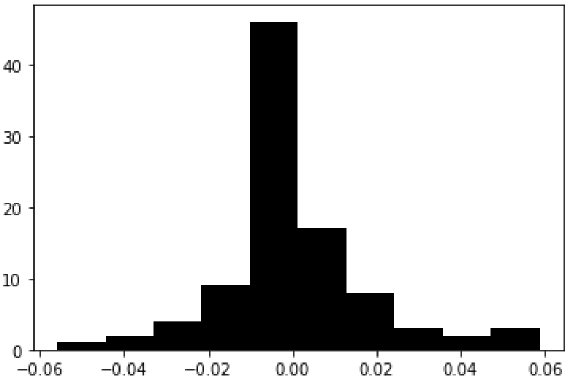
Column 1



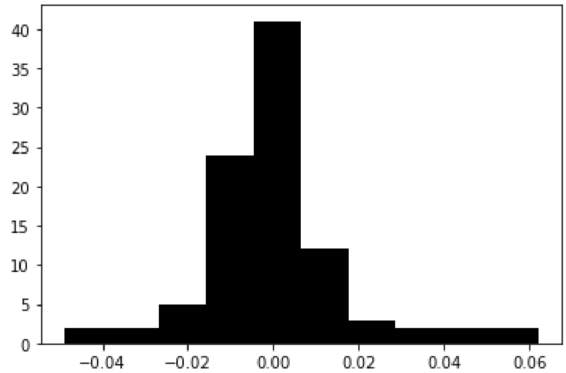
Column 2



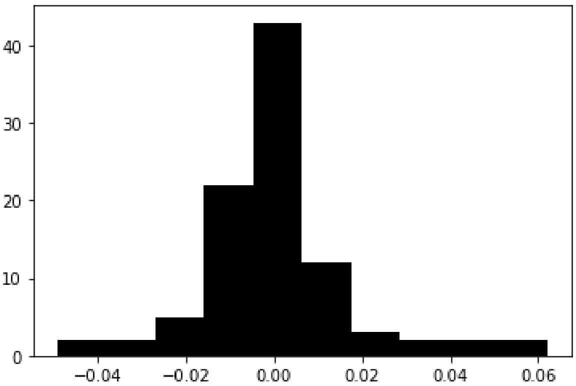
Column 3



Column 4



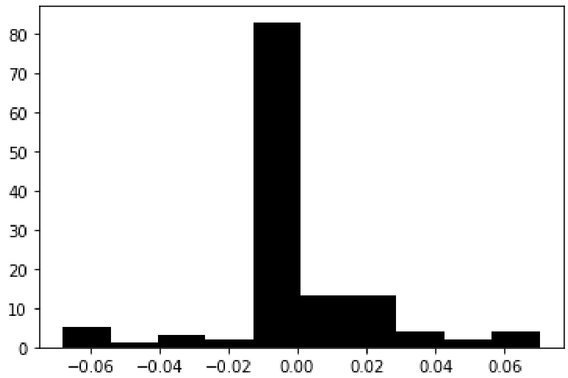
Column 5



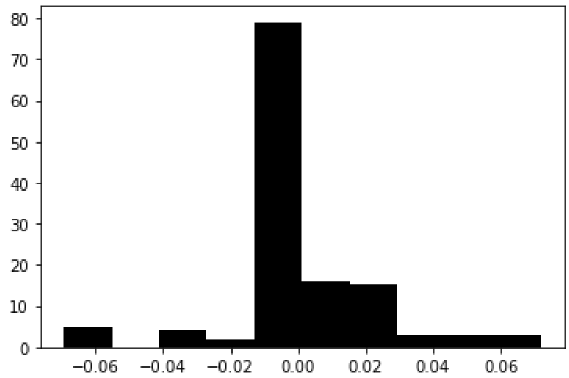
Notes: Figure A.5 shows the histograms of residuals for each column in the bank-level panel analysis testing the effect of BNPL Sales on credit cards as a fraction of total assets.

FIGURE A.6: HISTOGRAMS OF RESIDUALS FOR PANEL ANALYSIS IN TABLE 10

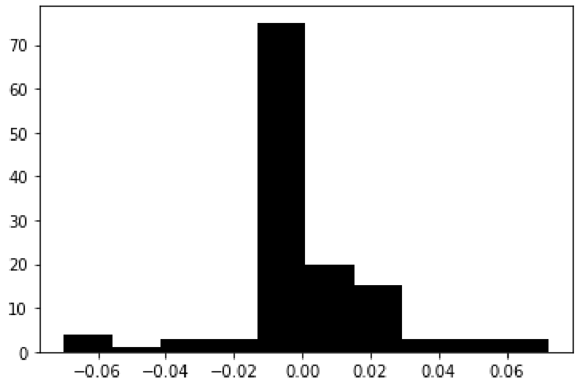
Column 1



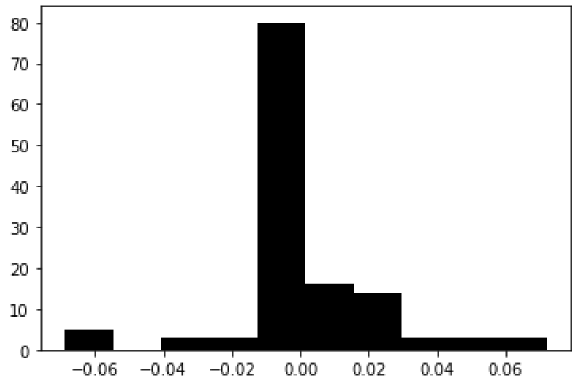
Column 2



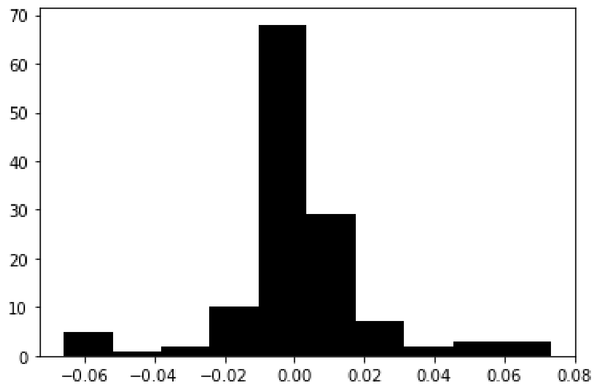
Column 3



Column 4



Column 5



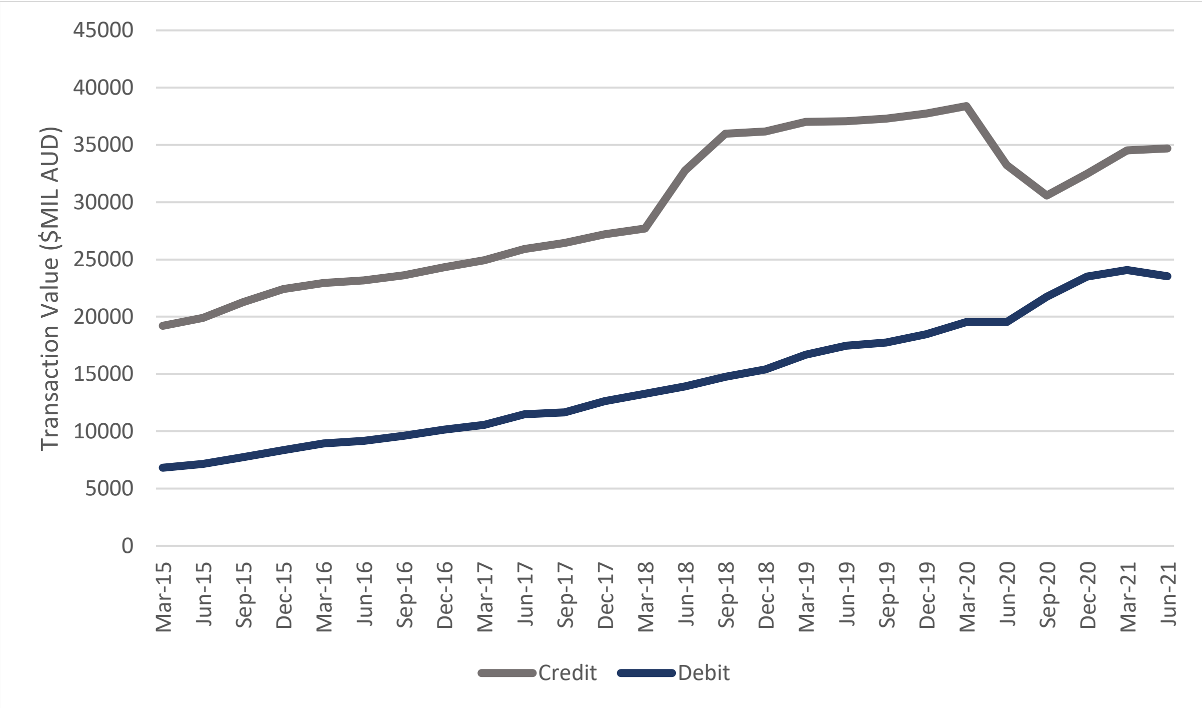
Notes: Figure A.6 shows the histograms of residuals for each column in the bank-level panel analysis testing the effect of BNPL Customers on credit cards as a fraction of total assets.

Table A.8: Descriptive Statistics of E-Commerce Case Study Variables

Variable	Obs.	Mean	Std	Min	0.25	0.5	75%	Max
APT Sales	16	0.20	0.05	0.11	0.16	0.22	0.23	0.28
E-Com Credit	26	0.37	0.07	0.26	0.30	0.36	0.44	0.44
E-Com Debit	26	0.17	0.04	0.11	0.14	0.17	0.20	0.23

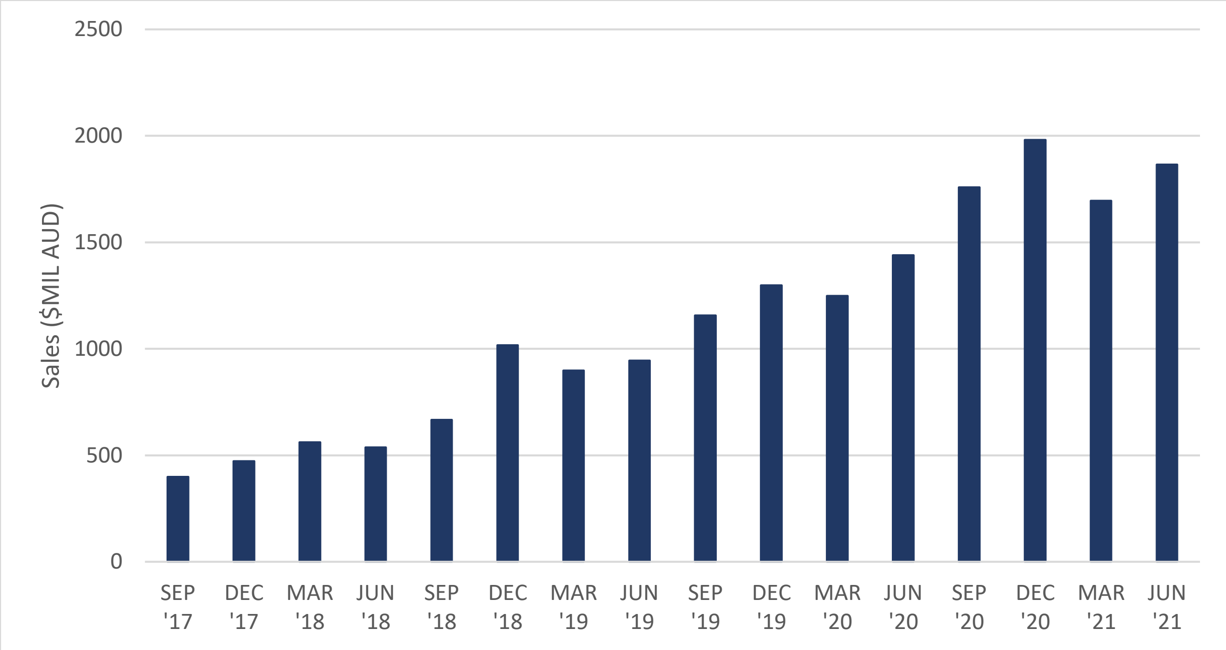
Notes: Table A.8 shows the descriptive statistics of the new variables used in the E-Commerce case study. APT Sales is the online portion of Afterpay sales as a fraction over total online retail sales in Australia. E-Com Credit is the portion of 'Device not present' credit transactions over total credit transaction value. E-Com Debit is the portion of 'Device not present' debit transactions over total debit transaction value.

Figure A.7: Credit and Debit 'Device not Present' Transactions



Notes: Figure A.7 depicts the 'Device not present' credit and debit transactions. Debit maintains a steady trajectory, however, credit suddenly jumps in 2018 and falls in 2020.

FIGURE A.8: SEASONALLY ADJUSTED TIME SERIES OF AFTERPAY ONLINE SALES



Notes: Figure A.8 shows the online sales portion of Afterpay ANZ sales which follows a steady incline. Majority of Afterpay sales have been online, only recently has this number started to change as the business expands and is accepted by more brick-and-mortar merchants.

TABLE A.9: PEARSON'S CORRELATION MATRIX FOR E-COMMERCE CASE STUDY VARIABLES

	APT Sales	E-Com Credit	E-Com Debit	COVID	Syd LD	Mel LD
APT Sales	1.00					
E-Com Credit	0.76	1.00				
E-Com Debit	0.77	0.95	1.00			
COVID	0.51	0.56	0.71	1.00		
Syd LD	0.23	0.31	0.40	0.53	1.00	
Mel LD	0.52	0.44	0.51	0.78	0.28	1.00

Notes: Table A.9 shows the correlation matrix between the variables used in the E-Commerce case study. APT Sales is the online portion of Afterpay sales as a fraction over total online retail sales in Australia. E-Com Credit is the portion of 'Device not present' credit transactions over total credit transaction value. E-Com Debit is the portion of 'Device not present' debit transactions over total debit transaction value. COVID represents a binary variable that shows the existence of the COVID-19 virus. Syd LD and Mel LD are binary variables for times when Sydney and Melbourne were under lockdown/heavy restrictions.

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