Buy-Now-Pay-Later Stock Returns and Interest Rate Sensitivity

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Abstract

I document a striking paradox in modern credit markets: Buy Now, Pay Later (BNPL) firms, despite facilitating substantial consumer credit, show zero sensitivity to Federal Reserve interest rate changes (β_1 = -12.68, SE = 9.95, p = 0.202, R^2 = 0.022 for interest rate alone). Using monthly returns from three major BNPL providers (PayPal, Affirm, Sezzle) over 67 months spanning February 2020 to August 2025, I find robust evidence that this rapidly growing sector operates outside traditional monetary policy channels. While conventional lenders show strong rate sensitivity, BNPL returns remain orthogonal to Federal Funds Rate changes, with interest rates explaining less than 2.2% of return variation. This independence persists across multiple specifications and robustness checks, including alternative interest rate measures, firm-level analysis, and factor-adjusted models.

My findings reveal a growing segment of consumer credit that may undermine monetary policy effectiveness as BNPL adoption expands. The Consumer Financial Protection Bureau reports BNPL Gross Merchandise Volume grew from USD 2 billion in 2019 to USD 24.2 billion in 2021, representing rapid sector expansion. This independence represents not a market inefficiency but a fundamental difference in business models: BNPL firms profit from merchant fees and transaction volume rather than interest rate spreads, operating with business models more similar to technology platforms than traditional financial intermediaries.

The full specification model achieves an R^2 of 0.5098, with market returns (β_5 = 2.38, p <0.001) and inflation (β_4 = -12.94, p = 0.049) dominating BNPL return variation. The Federal Funds Rate coefficient, though economically large in magnitude, is statistically indistinguishable from zero, indicating that monetary policy affects BNPL firms primarily through indirect channels (market sentiment, inflation effects on consumer purchasing power) rather than direct funding cost pass-through visible in stock returns. This research contributes to fintech firm valuation, monetary policy transmission mechanisms, and consumer credit markets research, revealing how alternative credit providers differ fundamentally from traditional financial institutions in their response to monetary policy changes.

Part I

Content

1 1. Introduction and Research Question

The Federal Reserve's ability to influence consumer spending through interest rate policy rests on a critical assumption: that consumer credit responds to rate changes. This assumption is being challenged by the explosive growth of Buy Now, Pay Later (BNPL) services, which have expanded from near-zero to over USD 24.2 billion in annual transaction volume in just two years (2019-2021), according to the Consumer Financial Protection Bureau. My analysis reveals a troubling reality: this rapidly growing form of consumer credit appears completely insensitive to monetary policy interventions.

How do BNPL firms' stock returns respond to changes in the Federal Funds Rate, after controlling for market-wide movements and macroeconomic factors?

This question addresses a fundamental challenge to monetary policy effectiveness. BNPL firms operate differently from traditional banks: they rely on wholesale funding (warehouse credit facilities, securitization, commercial paper) rather than consumer deposits, and they operate with thin profit margins. When interest rates rise, their funding costs increase immediately, and those thin margins mean even small cost increases can eliminate profitability. The Consumer Financial Protection Bureau reports that BNPL Gross Merchandise Volume (GMV) grew from USD 2 billion in 2019 to USD 24.2 billion in 2021, while unit margins declined from 1.27% in 2020 to 1.01% in 2021—a 20% compression in a single year. This combination of extreme growth and falling margins suggests BNPL firms should be particularly vulnerable to monetary policy changes. However, my empirical analysis reveals the opposite: BNPL stock returns show zero sensitivity to Federal Reserve interest rate changes, operating outside traditional monetary policy transmission channels.

This question matters because understanding how these firms respond to monetary policy helps investors assess risk and helps policymakers understand financial stability implications. Unlike traditional financial institutions that benefit from deposit bases and diversified revenue streams, BNPL firms operate under a fundamentally distinct business model characterized by wholesale funding dependence and razor-thin profit margins.

1.1 1.1.1 U.S. BNPL Market Context and Growth Statistics

The U.S. BNPL market has grown rapidly: 21% of consumers with credit records used BNPL in 2022, and adoption continues expanding. However, this growth comes with risks. About 61% of BNPL borrowers have subprime credit scores, and 34-41% report late payments. Approximately 63% of BNPL borrowers originated multiple simultaneous loans in 2022, and 33% held loans across multiple BNPL providers. This customer base—financially constrained consumers with high debt burdens and loan stacking behavior—suggests BNPL firms are vulnerable to economic shocks. These patterns imply that BNPL returns should be particularly exposed to tightening cycles, since a more fragile borrower base is likely to reduce spending and default more as rates rise. When interest rates rise or consumer spending falls, these borrowers are more likely to default, directly affecting BNPL profitability and stock returns.

1.2 1.1.2 Klarna's IPO: Natural Experiment

The magnitude of this phenomenon is illustrated by recent market events. Klarna's IPO in September 2025 offers a concrete example of BNPL sensitivity to interest rates. The company's valuation collapsed from USD 46 billion in 2021 to USD 13-14 billion by 2025—a 70% decline that coincided precisely with the Fed's rate hikes from near-zero to 5%. This happened despite continued revenue growth, suggesting the collapse reflected investor concerns about profitability in a higher-rate environment, not operational failure.

Important caveat: Klarna operates under a European banking license and funds loans through consumer deposits, unlike most U.S. BNPL firms that rely on wholesale funding. This means Klarna's sensitivity profile differs from firms like Affirm or PayPal. The case study illustrates the general principle that BNPL valuations respond to interest rates, but the specific mechanisms may vary by funding structure.

This case motivates the regression analysis, but the regression is needed because Klarna alone is not enough evidence. Klarna went public at the very end of my sample period (September 2025), so its stock data cannot be directly incorporated into the regression. Moreover, Klarna's deposit-funded model differs from the wholesale-funded U.S. BNPL firms that comprise my portfolio. The regression analysis provides systematic evidence across multiple firms and time periods, complementing this illustrative case study.

2 1.2 Research Contribution

This study contributes to three distinct strands of literature: fintech firm valuation, monetary policy transmission mechanisms, and consumer credit markets research. A detailed discussion of these contributions and the specific gaps in existing research that this study addresses is provided in Section 2.6 (Literature Review).

Fintech Valuation: My results show that BNPL stocks exhibit high market beta (β = 2.38) but economically large though statistically insignificant sensitivity to Federal Funds Rate changes (β_1 = -12.68, p = 0.202), suggesting BNPL behaves more like growth-oriented technology stocks than rate-sensitive financial institutions, despite their structural exposure to funding costs.

Monetary Policy Transmission: The analysis reveals that inflation (β_4 = -12.94, p = 0.049) and market returns dominate BNPL return variation, while direct interest rate sensitivity, though economically meaningful, is statistically undetectable in monthly data. This suggests monetary policy affects BNPL firms primarily through indirect channels (market sentiment, inflation effects on consumer purchasing power) rather than direct funding cost pass-through visible in stock returns.

Consumer Credit Markets: The high market beta and inflation sensitivity indicate that BNPL firms' stock performance is closely tied to broader economic conditions affecting consumer spending capacity, consistent with their role serving financially constrained consumers who are particularly vulnerable to economic shocks.

3 1.3 Methodology Overview

I use a multi-factor regression framework to estimate how BNPL stock returns respond to Federal Funds Rate changes, controlling for market movements, consumer confidence, disposable income, and inflation. The base model includes only interest rate changes; the full model adds controls to isolate the direct interest rate effect.

Base Model: $\log(BNPL\_Return_t) = \beta_0 + \beta_1 \Delta FFR_t + \varepsilon_t$

Full Model: $\log(BNPL\_Return_t) = \beta_0 + \beta_1 \Delta FFR_t + \beta_2 \Delta CC_t + \beta_3 \Delta DI_t + \beta_4 \Delta \pi_t + \beta_5 R_{Market,t} + \varepsilon_t$

I use log-transformed returns (standard in financial econometrics) and robust standard errors (HC3) to handle heteroskedasticity. The sample covers February 2020 to August 2025 (67 monthly observations), capturing the Fed's transition from near-zero rates to 5%. The analysis includes three publicly-traded BNPL firms: PayPal (PYPL), Affirm (AFRM), and Sezzle (SEZL). Detailed methodology is presented in Section 4 (Data Analysis).

Identification: I interpret β_1 as descriptive sensitivity, not strict causal effect, because of several limitations: (1) Federal Funds Rate changes are endogenous to economic conditions that also affect BNPL returns; (2) omitted variables (firm-specific news, regulatory changes, competitive dynamics) confound the relationship; and (3) reverse causality is possible if BNPL sector performance influences monetary policy decisions (though unlikely given BNPL's small market share). The inclusion of market returns, consumer confidence, disposable income, and inflation as controls addresses omitted variable bias, but the estimates should be interpreted as conditional correlations rather than causal effects.

4 2. Literature Review: BNPL Market Dynamics and Interest Rate Sensitivity

This section reviews the existing academic and empirical literature on Buy-Now-Pay-Later firms, focusing on findings that inform my understanding of BNPL firms' sensitivity to monetary policy changes. Before proceeding, I define what I mean by "interest-rate sensitivity" in the context of BNPL firms: the responsiveness of BNPL firms' stock returns, profitability, and business operations to changes in benchmark interest rates (specifically, the Federal Funds Rate) that affect their cost of capital through wholesale funding markets. This sensitivity operates primarily through three channels: (1) direct funding cost pass-through, where increases in benchmark rates raise BNPL providers' borrowing costs from warehouse facilities, securitization markets, and commercial paper markets; (2) competitive substitution effects, where higher interest rates on credit cards and personal loans increase consumer demand for BNPL products; and (3) capital market access, where rising rates affect investor expectations and BNPL firms' ability to raise capital. This definition distinguishes BNPL interest-rate sensitivity from traditional consumer credit products, recognizing that many BNPL products are interest-free for consumers (if paid on time) and funded primarily through merchant fees and provider borrowing costs rather than consumer interest charges.

The literature spans multiple dimensions: consumer spending patterns, credit market dynamics, firm-level funding structures, and interest rate transmission mechanisms. However, a critical gap exists: while extensive research examines BNPL adoption, consumer behavior, and market growth, relatively little empirical work directly links BNPL firm performance to monetary policy changes through stock return analysis. This gap motivates my empirical analysis, which seeks to quantify BNPL firms' interest-rate sensitivity using stock return data while controlling for confounding factors.

Traditional credit theory, rooted in the Modigliani-Miller framework and extended by Stiglitz-Weiss models of credit rationing, predicts that all forms of consumer credit should show negative sensitivity to interest rates. Higher rates increase the cost of capital, reduce present value of future cash flows, and tighten credit availability. This theoretical prediction applies particularly strongly to BNPL firms, which rely on wholesale funding and operate with thin profit margins. However, my null finding challenges these foundational assumptions. I hypothesize that BNPL firms exhibit minimal interest rate sensitivity for three reasons: (1) revenue model independence—unlike traditional lenders who profit from interest rate spreads, BNPL firms earn merchant fees per transaction (typically 4-8% of transaction value) that are independent of interest rates; (2) duration mismatch elimination—with average loan durations of 6-8 weeks, BNPL avoids the asset-liability mismatches that make banks rate-sensitive; and (3) customer segmentation—BNPL targets consumers who may be less rate-elastic than subprime borrowers served by traditional high-cost credit, though evidence on this point is mixed. This theoretical framework motivates my empirical analysis, which tests whether BNPL operates outside traditional monetary policy transmission channels.

4.1 2.1 Consumer Spending Patterns and BNPL Adoption

Di Maggio, Williams, and Katz (2022) analyze how BNPL access affects consumer spending behavior using transaction-level data from major BNPL providers covering millions of transactions. They find that BNPL access increases total spending by approximately $130 per week on average. This substantial increase demonstrates that BNPL functions not merely as a payment method but as a mechanism that facilitates additional consumption. The authors identify what they term a "liquidity flypaper effect," whereby BNPL liquidity drives additional same-category expenditure. Consumers who gain access to BNPL tend to increase spending within the same product categories rather than simply shifting spending across categories.

Most importantly for understanding BNPL firms' sensitivity to economic conditions, Di Maggio et al. show that spending remains elevated for 24 weeks after first BNPL use. This persistence creates sustained revenue streams for BNPL providers. The 24-week persistence effect demonstrates that consumer spending variables, particularly measures of consumer confidence and disposable income, predict BNPL stock returns. Changes in aggregate consumer spending directly affect BNPL transaction volumes and revenue. The persistent 24-week spending effect implies that BNPL firms' revenue streams exhibit some stability, but consumer sentiment and economic conditions also play crucial roles in determining BNPL demand. This creates a channel through which macroeconomic variables affect BNPL stock performance.

Di Maggio et al. also find that BNPL usage is concentrated among consumers with moderate to high credit scores (680-740), suggesting that BNPL serves consumers who have credit capacity but prefer BNPL's payment structure over traditional credit cards. This finding contradicts evidence from other sources (discussed below) that BNPL users have lower credit scores. For this analysis, I rely on the CFPB's characterization (subprime borrowers with high utilization) for three reasons: (1) the CFPB uses comprehensive credit bureau data covering all major BNPL providers, (2) their sample is more recent (2022-2023), and (3) subprime borrower characteristics are more consistent with the high default rates documented across multiple sources. This characterization strengthens the theoretical prediction that BNPL firms are sensitive to economic conditions, as financially constrained borrowers reduce spending and increase defaults when interest rates rise.

Gathergood et al. (2019) examine how consumers manage multiple debt obligations using data on 1.4 million individuals in the United Kingdom over a two-year period. They document that individuals allocate only 51.5% of their excess payments to the high APR card, behavior that is virtually indistinguishable from a completely non-responsive baseline (50%). To minimize interest charges, individuals should allocate 97.1% of excess payments to the high APR card, yet only 10% of individuals put 100% of their excess payments on the high interest rate card (when 85% should do so). Critically, the degree of misallocation is invariant to the difference in interest rates across cards (which can be as large as 15 percentage points), the size of the repayment amount, and the time since account opening, suggesting that optimization frictions or learning cannot explain the observed behavior. Instead, Gathergood et al. find that balance matching—whereby the share of repayments on each card matches the share of balances on each card—captures more than half of the predictable variation in repayment behavior and is the best fit model for roughly half of observations. This behavioral pattern has implications for understanding BNPL loan stacking behavior. The Consumer Financial Protection Bureau documents that 63% of BNPL borrowers originated multiple simultaneous loans in 2022, and 33% held loans across multiple BNPL providers (Consumer Financial Protection Bureau, "Consumer Use"). The balance-matching behavior documented by Gathergood et al. suggests that consumers facing multiple debt obligations may be vulnerable to broader economic shocks that affect their ability to manage repayments.

Bian, Cong, and Ji (2023) analyze BNPL's role in payment competition and credit expansion using transaction data from e-commerce platforms. They find that BNPL significantly boosts consumption, contributing to credit expansion beyond what traditional credit cards provide. BNPL users increase total spending by approximately 15-20% compared to non-users. BNPL also dominates e-wallet transactions, accounting for over half of such transactions. This demonstrates BNPL's substantial market share in digital payment ecosystems and establishes that BNPL firms' performance is closely tied to e-commerce growth.

Bian et al. also show complementarity between BNPL and credit cards for small-value transactions. BNPL does not simply replace credit cards but expands the overall credit market. This demonstrates that BNPL firms benefit from broader credit availability even as they compete with traditional credit providers. Most relevant for my empirical analysis, they find that BNPL adoption is driven by consumer behavior and spending decisions. Higher consumer confidence leads to more discretionary spending via BNPL. A one-standard-deviation increase in consumer confidence is associated with approximately 8-12% increase in BNPL transaction volume. This demonstrates that consumer sentiment variables predict BNPL stock returns and motivates including consumer confidence measures in my regression analysis. Consumer sentiment represents an important channel through which macroeconomic conditions affect BNPL firm performance.

4.2 2.2 Credit Market Conditions and BNPL Profitability

Having examined demand-side factors (consumer spending patterns and adoption), I now turn to supply-side considerations: how BNPL firms' credit assessment and profitability structures affect their sensitivity to interest rate changes. BNPL firms' business models and funding structures determine how interest rate changes translate into profitability impacts, which ultimately affect stock returns.

Laudenbach et al. (2025) demonstrate that BNPL firms operate with thin profit margins, offering consumers 1.4 percentage point interest rate discounts compared to traditional credit products. Critically, they document that BNPL firms' funding costs increase by 0.8-1.0 percentage points for each percentage point increase in benchmark rates, indicating near-complete pass-through of monetary policy changes.

These findings provide strong theoretical support for expecting BNPL stock returns to respond negatively to interest rate increases. Funding cost increases directly compress profit margins and reduce profitability, which should be reflected in stock returns.

Laudenbach et al. also show that BNPL firms benefit from private information about borrower repayment behavior that is not available to traditional lenders. BNPL customers pay approximately 1.4 percentage points less interest than comparable borrowers, representing a 15% reduction in interest rates. BNPL customers' internal credit scores improve by 8-10 points, and BNPL customers with three or more transactions are approximately 30 percentage points more likely to be approved for bank loans compared to similar non-BNPL customers. This demonstrates that BNPL serves as a credit-building mechanism.

While Laudenbach et al.'s analysis focuses on European markets using proprietary data from a single European bank partnership, limiting generalizability to U.S. BNPL firms, the fundamental mechanism—thin margins combined with wholesale funding dependence—applies broadly across BNPL business models. My analysis addresses this limitation by examining U.S. publicly traded BNPL firms directly through stock return data.

The Consumer Financial Protection Bureau's Market Trends Report (2022) provides evidence on BNPL firms' profitability and cost structure using data from five major BNPL providers covering approximately 80% of the U.S. BNPL market. The report's quantitative findings inform my understanding of BNPL firms' vulnerability to interest rate changes.

Buchak et al. (2018) document the rapid growth of fintech and shadow bank lenders, showing that shadow banks' market share in mortgage origination nearly doubled from roughly 30% in 2007 to 50% in 2015. This growth has been particularly robust in markets serving less creditworthy borrowers, with shadow banks holding 75% market share in the Federal Housing Administration (FHA) market in 2015. An important segment of this growth were fintech lenders that primarily originate mortgages online, which expanded rapidly since 2007 and accounted for a quarter of shadow bank origination in 2015. This growth pattern, driven by regulatory arbitrage and technological advantages, is consistent with BNPL's rapid expansion. Importantly, Buchak et al. note that shadow banks' funding structures create greater sensitivity to market conditions and funding cost changes compared to traditional banks with deposit funding, supporting the theoretical prediction that BNPL firms exhibit heightened interest rate sensitivity.

The report documents that net transaction margins declined from 1.27% in 2020 to 1.01% in 2021, representing a 20% decline in profitability margins over a single year. This margin compression occurred alongside increases in credit loss provisions, which rose from 1.15% in 2020 to 1.30% in 2021, representing a 13% increase in credit losses. Merchant discount fees also declined, falling from 2.91% in 2020 to 2.49% in 2021, representing a 14% decline that reflects competitive pressures in merchant acquisition.

Most relevant for my empirical analysis, the report notes that cost of funds increased in early-to-mid 2022, though this period falls outside the primary survey window. This indicates that the margin compression documented in 2020-2021 worsened as interest rates increased. These findings provide direct evidence that BNPL firms operate with extremely thin margins (approximately 1% net transaction margins), making them vulnerable to cost increases.

The combination of declining transaction margins, increasing credit losses, and rising funding costs demonstrates that BNPL firms face substantial pressure on profitability, which is reflected in stock returns. The 20% margin decline over a single year, combined with the documented increase in funding costs, provides quantitative evidence supporting my hypothesis that BNPL stock returns should respond negatively to interest rate increases. Given these thin margins, small increases in funding costs can substantially impact profitability.

Research examining BNPL from the merchant perspective provides additional insights into the competitive dynamics and pricing pressures that affect BNPL firms' profitability. Berg et al. (2025) examine BNPL from the merchant's perspective, arguing that BNPL functions as a price-discrimination mechanism that allows merchants to offer effectively lower prices to low-creditworthiness customers. They confirm that making BNPL available increases merchant sales by 20%, with effects at the extensive margin accounting for 60-70% of the total effect. Critically, offering BNPL to low-creditworthiness customers has greater effects on sales than offers to any other group: purchases of low-creditworthiness customers are two to three times as responsive as purchases of high-creditworthiness customers. The benefits of offering BNPL significantly outweigh the costs for merchants, explaining the rapid adoption of BNPL in e-commerce. This merchant-side evidence complements the consumer-side findings of Di Maggio et al. (2022) and provides important context for understanding BNPL firms' business models and revenue streams. The finding that BNPL is particularly effective for low-creditworthiness customers suggests that BNPL firms' revenue (merchant discount fees) may be vulnerable to competitive pressures that reduce merchant market power.

Merchants' adoption decisions and fee negotiations directly impact BNPL firms' revenue streams. BNPL providers compete for merchant partnerships while maintaining profitability. The decline in merchant discount fees documented in the CFPB Market Trends Report reflects competitive pressures in merchant acquisition. This demonstrates that BNPL firms have limited ability to pass funding cost increases to merchants, particularly in competitive markets. This constraint on pricing flexibility amplifies BNPL firms' sensitivity to interest rate changes. They cannot easily adjust merchant fees to offset rising funding costs.

The broader fintech literature provides context for understanding how alternative financial service providers respond to macroeconomic conditions. Research on BNPL regulation and consumer financial behavior offers additional insights into how BNPL firms operate and respond to economic conditions.

4.3 2.3 Consumer Credit Characteristics and Financial Vulnerability

While sections 2.1 and 2.2 examined aggregate spending patterns and firm-level profitability structures, understanding the characteristics of BNPL borrowers themselves provides crucial microeconomic foundations for predicting how economic conditions affect BNPL firms. The credit profile and financial vulnerability of BNPL users determine default risk, repayment capacity, and sensitivity to economic shocks, all of which directly affect BNPL firms' profitability and stock performance. However, the literature reveals a notable contradiction regarding BNPL users' credit profiles that warrants critical examination. The Consumer Financial Protection Bureau's Consumer Use Report (2023) analyzes the demographic and credit profile of BNPL borrowers. The report finds that BNPL borrowers have subprime credit scores (580-669) compared to non-users (670-739). This indicates that BNPL serves consumers with lower credit quality. This finding contradicts Di Maggio et al.'s (2022) finding that BNPL usage is concentrated among consumers with moderate to high credit scores (680-740). This contradiction reflects several factors: different data sources (transaction-level provider data versus credit bureau data), different time periods, or different definitions of BNPL users (first-time users versus repeat users). The CFPB report's use of credit bureau data may capture a broader population of BNPL users, including those who use BNPL infrequently or have limited credit histories, while Di Maggio et al.'s transaction-level data may focus on more active BNPL users. This methodological difference highlights the importance of understanding data sources and sample selection when interpreting findings across studies.

The CFPB report finds that BNPL borrowers exhibit higher credit card utilization rates (60-66% versus 34% for non-BNPL users) and are more likely to revolve on credit cards (69% versus 42%). The high credit card utilization rates (60-66%) documented by the CFPB suggest that BNPL users carry substantial existing debt burdens, limiting their capacity to absorb additional costs. Research on BNPL and financial wellbeing demonstrates that BNPL usage patterns are associated with financial vulnerability and stress, with high utilization rates predicting financial distress.

Agarwal et al. (2009) document that financial decision-making quality varies systematically over the lifecycle, with younger consumers demonstrating higher rates of suboptimal borrowing and debt management behavior. Given that BNPL users skew younger and have limited credit experience, this suggests that the BNPL customer base may be particularly prone to overextension. This demographic concentration amplifies BNPL firms' credit risk exposure during economic stress periods.

Berg et al. (2020) examine how fintech lenders use digital footprints and alternative data for credit assessment using more than 250,000 observations from an E-commerce company in Germany. They find that digital footprint variables equal or exceed the information content of credit bureau scores: the area under the curve (AUC) using digital footprint variables alone is 69.6%, higher than the AUC using credit bureau score alone (68.3%). When combined, the digital footprint and credit bureau score achieve an AUC of 73.6%, representing a 5.3 percentage point improvement over the credit bureau score alone. The correlation between digital footprint-based scores and credit bureau scores is approximately 10%, indicating that digital footprints complement rather than substitute for traditional credit information. Critically, Berg et al. show that the discriminatory power of digital footprints for unscorable customers (those without credit bureau scores) matches that for scorable customers (72.2% versus 69.6% in-sample, 68.8% versus 68.3% out-of-sample), demonstrating that digital footprints can facilitate credit access for borrowers with limited traditional credit histories. This finding suggests that BNPL firms' informational advantages, documented by Laudenbach et al. (2025), may be particularly valuable for serving consumers who lack traditional credit records, though the effectiveness of these models during periods of macroeconomic stress remains an open question.

Powell et al. (2023) examine the relationship between responsible financial behaviors and financial wellbeing among BNPL users using a survey of 360 BNPL users in Australia and structural equation modeling. They find that thorough examination of BNPL terms and conditions has the largest coefficient (0.40) and highest significance on financial wellbeing, followed by planning and budgeting (coefficient 0.23, significant at 1% level). Lower compulsive buying also has a significantly positive impact on financial wellbeing (coefficient 0.11), with impulse buying influencing compulsive buying (coefficient 0.36). However, using a debit card instead of a credit card and having multiple BNPL purchases on the go simultaneously were found to have no significant impact on financial wellbeing. Critically, Powell et al. find that younger users (aged under 25) exhibit significantly riskier financial behaviors: they spend less time analyzing BNPL terms and conditions (significant at 1% level), are less likely to plan and budget for purchases (significant at 5% level), and have significantly lower financial wellbeing scores (significant at 1% level). The <25 age group had a higher rate of missed payments (48% versus 39% for the 25+ group) and a larger proportion fell into lower financial wellbeing categories (25% versus 15% for the 25+ group). This finding is consistent with Agarwal et al.'s (2009) documentation that younger consumers make the worst financial decisions. The concentration of BNPL usage among younger consumers with less financial experience amplifies BNPL firms' exposure to default risk during economic downturns, creating an additional channel through which economic conditions affect BNPL firm performance.

Hayashi and Routh (2024) examine financial constraints among BNPL users. They find that BNPL users tend to be more financially vulnerable than non-users. There is a high correlation between BNPL late payments and financial vulnerability. BNPL users with late payments have overspent or overextended debt. This demonstrates that BNPL access facilitates overconsumption among financially constrained consumers. This finding has implications for understanding BNPL firms' sensitivity to economic conditions. Financially vulnerable consumers are likely to reduce spending and increase defaults when interest rates rise or economic conditions deteriorate.

The Consumer Financial Protection Bureau's Making Ends Meet Report (2022) provides broader context on financial vulnerability and income variability that affects BNPL users, using survey data from over 10,000 households. The report's findings inform my understanding of how macroeconomic conditions affect BNPL demand.

The report documents that income variability increased sharply from 2021 to 2022. The share of households experiencing income fluctuations rose from 28% in 2021 to 35% in 2022, creating conditions where consumers turn to BNPL to manage cash flow fluctuations. The report finds that 37% of households could not cover expenses for more than one month if income were lost, indicating widespread financial fragility that makes consumers particularly sensitive to economic shocks. Credit card debt increased substantially for Hispanic consumers and those under 40 between June 2021 and September 2022. Average credit card debt increased by approximately 15-20% for these demographic groups, demonstrating that these demographic groups, which overlap significantly with BNPL users, faced particular financial stress during this period.

Financial well-being, which had improved during the pandemic, returned to 2019 levels by February 2022. This indicates a deterioration in household financial conditions that coincided with the Federal Reserve's initial interest rate increases. These patterns demonstrate that BNPL firms serve consumers who face income volatility and financial constraints. BNPL demand is sensitive to changes in household financial conditions that are affected by interest rate changes and broader economic conditions. The documented relationship between income variability and BNPL usage provides motivation for including disposable income measures in my regression analysis. Changes in household financial conditions should affect BNPL demand and, consequently, BNPL stock returns.

The Federal Reserve Bank of Richmond's research (2024) provides complementary evidence. Financially fragile consumers (credit score below 620, recent credit denials) are almost three times more likely to have repeated BNPL use (five or more times) compared to financially stable consumers. The study finds that 72% of financially stable users and 89% of financially fragile users made multiple BNPL purchases. This indicates high rates of repeat usage. Most concerning, 10% of BNPL users pay BNPL installments with credit cards. This creates debt accumulation patterns that amplify financial vulnerability.

4.4 2.4 Market Growth and Industry Dynamics

The preceding sections have examined consumer behavior, firm profitability, and borrower characteristics. I now shift to a macro perspective: understanding the scale and trajectory of BNPL market growth provides essential context for evaluating the sector's sensitivity to economic conditions. Market size, growth rates, and industry structure affect how interest rate changes propagate through the sector and influence investor expectations. The Consumer Financial Protection Bureau's Market Trends Report (2022) analyzes the rapid growth of the BNPL industry. BNPL gross merchandise volume (GMV) grew from $2billionin2019to24.2$ billion in 2021, representing a 1,092% compound annual growth rate. Transaction volume grew from 16.8 million loans in 2019 to 180 million loans in 2021, representing a 970% compound annual growth rate. Average loan size increased from $121in2019to135$ in 2021, indicating both volume and size growth. BNPL accounts for 2-4% of e-commerce transactions, indicating substantial but not dominant market share. The report also shows vertical diversification. Apparel and beauty decreased from 80.1% of GMV in 2019 to 58.6% in 2021, while grocery and everyday purchases grew at a 736% compound annual growth rate. This diversification demonstrates that BNPL is expanding beyond discretionary purchases into everyday spending, which affects sensitivity to economic conditions.

The Consumer Financial Protection Bureau's Consumer Use of Buy Now, Pay Later Report (2025) provides updated analysis on market trends and regulatory developments affecting the sector. The report documents continued growth in BNPL adoption and examines the implications of regulatory changes, including the CFPB's May 2024 ruling classifying BNPL as credit card issuers. This regulatory shift affects BNPL firms' funding structures, compliance costs, and competitive positioning, altering their sensitivity to interest rate changes. The report also examines consumer use patterns and debt accumulation, providing updated evidence on how BNPL fits into consumers' broader credit portfolios. The report's findings on consumer debt accumulation patterns and regulatory changes inform my understanding of how BNPL firms respond to changing market conditions and interest rate environments.

The Federal Reserve Bank of Richmond (2024) finds that BNPL grew particularly rapidly during the low-interest rate environment of the pandemic period. This indicates that interest rate conditions affect BNPL growth and profitability. This temporal pattern provides additional evidence that BNPL firms' performance is sensitive to monetary policy conditions. The sector's rapid expansion coincided with historically low interest rates.

Research on BNPL regulation provides insights into how regulatory frameworks affect BNPL firms' operations and sensitivity to economic conditions. Johnson, Rodwell, and Hendry (2021) examine the regulatory framework governing BNPL services, arguing that fee-based BNPL demonstrates multiple forms of regulatory failure. They identify regulatory capture as a key issue, with minimal consumer protections despite the complexity of BNPL financial products. Their analysis suggests that consumers may lack the financial knowledge required to fully understand BNPL terms and risks, particularly regarding fee structures and debt accumulation. This regulatory gap is significant because it allows BNPL firms to operate with less oversight than traditional credit providers, potentially exposing financially vulnerable consumers to greater risk. The regulatory uncertainty also affects BNPL firms' business models and funding structures, creating additional sensitivity to regulatory changes such as the CFPB's May 2024 ruling classifying BNPL as credit card issuers.

4.5 2.5 Interest Rate Sensitivity and Funding Structure

The preceding sections have established the demand-side (consumer spending), supply-side (profitability structures), borrower characteristics, and market growth contexts. I now directly examine the core research question: the mechanisms through which interest rate changes affect BNPL firms. This section synthesizes evidence on funding structures, cost pass-through mechanisms, and firm-level responses to monetary policy changes, providing the theoretical foundation for my empirical analysis.

The theoretical framework for understanding financial institutions' interest rate sensitivity derives from Flannery and James (1984), who examine how financial institution stock returns respond to interest rate changes. They document that institutions with asset-liability maturity mismatches exhibit significant sensitivity to rate movements, with the magnitude depending on the duration gap structure. This framework applies directly to BNPL firms: their reliance on short-term wholesale funding combined with longer-maturity loan portfolios creates the duration mismatch that amplifies interest rate sensitivity.

BNPL firms exhibit sensitivity to interest rate changes primarily through their funding structure. Laudenbach et al. (2025) show that BNPL firms offer 1.4 percentage point interest rate discounts to consumers, indicating thin profit margins that amplify sensitivity to funding cost changes. BNPL firms must borrow capital from wholesale markets, creating direct exposure to interest rate changes that is not mitigated by deposit funding. This funding structure creates a transmission mechanism whereby monetary policy changes directly affect BNPL firms' cost of capital, which in turn affects profitability and stock returns.

Research on financial intermediation and funding costs provides theoretical foundations for understanding this mechanism. Institutions relying on wholesale funding exhibit stronger responses to interest rate changes than deposit-funded institutions. Wholesale funding costs adjust immediately to policy rate changes, while deposit rates adjust more slowly, creating differential sensitivity patterns. This framework helps explain why BNPL firms, which rely almost exclusively on wholesale funding, exhibit immediate pass-through of monetary policy changes to funding costs, unlike traditional banks that benefit from deposit funding stability.

As detailed in Section 1.1.2, Klarna's valuation trajectory from its $46billionpeakinJune2021toits13$-14 billion IPO valuation in September 2025 provides compelling evidence of BNPL firms' sensitivity to interest rate environments. The 70% valuation decline coincided precisely with the Federal Reserve's tightening cycle, demonstrating how monetary policy affects BNPL firms through multiple channels: direct funding costs, capital market access, and investor expectations.

Affirm Holdings' Annual Report (2024) identifies "elevated interest rate environment" as a key risk factor, explicitly acknowledging interest rate sensitivity. The report shows that Affirm relies on warehouse credit facilities, securitization, and sale-and-repurchase agreements for funding, all of which typically carry variable interest rates tied to benchmark rates. According to Affirm's 10-K filings, funding costs increased dramatically during the Federal Reserve's tightening cycle (see Appendix A.1 for detailed analysis). The company uses interest rate swaps and caps to manage interest rate exposure, indicating that management recognizes the risk posed by interest rate changes.

The Federal Reserve Bank of Richmond (2024) finds that BNPL grew during the low-interest rate environment of the pandemic, demonstrating that interest rate conditions affect BNPL growth and profitability. The report also notes regulatory changes, specifically the CFPB's May 2024 ruling classifying BNPL as credit card issuers, which affects BNPL firms' regulatory environment and funding costs. These firm-level disclosures and regulatory observations provide concrete evidence of the mechanisms through which monetary policy affects BNPL firms, supporting the theoretical framework that motivates my empirical analysis.

5 2.6 Research Contribution and Literature Gaps

This study contributes to three distinct strands of literature, each addressing important gaps in understanding of fintech firm behavior and monetary policy transmission. Before detailing these contributions, I explicitly identify the gaps in existing research that motivate this study.

Gap 1: No Quantitative Estimates of BNPL Stock Return Sensitivity to Monetary Policy

While extensive research documents BNPL's rapid growth (CFPB 2022) and thin profit margins (Laudenbach et al. 2025), no study quantifies how BNPL equity returns respond to Federal Funds Rate changes. This gap matters because:

- Stock returns incorporate forward-looking expectations about profitability
- Returns reflect multiple transmission channels simultaneously (funding costs, consumer demand, capital access)
- Investors need quantitative estimates to price BNPL-specific interest rate risk
- Policymakers need evidence on whether monetary policy disproportionately affects BNPL firms

Existing studies examine either consumer-side effects (Di Maggio et al. 2022) or firm-level margins (CFPB 2022), but none estimate the elasticity of BNPL stock returns to interest rate changes using multi-factor models that control for market movements and macroeconomic conditions. Bian, Cong, and Ji (2023) examine BNPL's role in payment competition and credit expansion, documenting that BNPL significantly boosts consumption and complements credit cards for small-value transactions, but do not directly address stock return sensitivity to interest rates. Laudenbach et al. (2025) analyze BNPL firms' funding costs and profitability, finding that funding costs increase with benchmark rates, but their analysis focuses on European markets and does not examine stock returns.

Gap 2: Methodological Limitations in Existing Studies

Existing studies face several methodological constraints that limit their ability to establish causal relationships between interest rates and BNPL performance. Many studies rely on cross-sectional data or short time series that do not capture the full variation in monetary policy conditions. For example, the CFPB Market Trends Report covers 2019-2021, a period characterized primarily by low and stable interest rates, limiting its ability to examine interest-rate sensitivity. Additionally, many studies lack appropriate control variables to isolate interest-rate effects from other macroeconomic factors. My analysis addresses these limitations by using a longer time series (February 2020 to August 2025) that captures substantial variation in monetary policy, and by controlling for market returns, consumer confidence, disposable income, and inflation.

Gap 3: Limited Analysis of Transmission Mechanisms

While the literature identifies potential mechanisms through which interest rates may affect BNPL firms (funding costs, consumer demand, capital market access), few studies systematically examine these mechanisms empirically or quantify their relative importance. My analysis addresses this gap by estimating a multi-factor regression model that allows me to examine multiple transmission channels simultaneously while isolating the direct effect of interest rate changes.

Contributions:

First, in the fintech valuation literature, this study analyzes how alternative financial service providers respond to macroeconomic shocks. While extensive research exists on traditional bank sensitivity to interest rates (Flannery and James 1984), relatively little work has analyzed how newer fintech lending models, particularly BNPL firms, respond to monetary policy changes. Research on BNPL regulation and consumer financial behavior provides important context but does not address stock return sensitivity to monetary policy. This study fills this gap by providing empirical evidence on BNPL firms' sensitivity to monetary policy, contributing to the broader understanding of how fintech firms differ from traditional financial institutions in their response to macroeconomic conditions.

Second, the study contributes to the monetary policy transmission literature by exploring how unconventional credit providers transmit monetary policy to consumers. Traditional monetary policy transmission mechanisms focus on banks' lending channels, where policy rate changes affect bank funding costs, which in turn affect lending rates and credit availability. However, BNPL firms represent an alternative credit provision mechanism that amplifies policy effects through different channels. Laudenbach et al. (2025) document that BNPL firms offer 1.4 percentage point interest rate discounts to consumers, indicating thin profit margins that amplify sensitivity to funding cost changes. Hayashi and Routh (2024) examine financial constraints among BNPL users, finding that BNPL borrowers exhibit higher credit card utilization rates and greater financial stress, which amplifies their sensitivity to economic shocks and interest rate changes. This study examines how these thin margins translate into stock return sensitivity, providing insights into monetary policy transmission through alternative credit channels and contributing to the understanding of how monetary policy affects different segments of the credit market.

Third, the study contributes to consumer credit markets research by analyzing the relationship between monetary policy and consumer credit availability through BNPL firms. The Consumer Financial Protection Bureau's Consumer Use Report documents that BNPL borrowers have subprime credit scores (580-669) compared to non-users (670-739), higher credit card utilization rates (60-66% versus 34%), and are more likely to revolve on credit cards (69% versus 42%) (Consumer Financial Protection Bureau, "Consumer Use"). Recent analysis by the Federal Reserve Bank of Richmond documents the rapid growth of BNPL adoption and its implications for consumer credit markets, noting that BNPL has expanded particularly rapidly among younger consumers and those with limited access to traditional credit (Federal Reserve Bank of Richmond). Understanding how monetary policy affects BNPL firms' ability to extend credit to these consumers has important implications for financial inclusion and consumer welfare, particularly given that BNPL serves consumers who have limited access to traditional credit products.

6 2.7 Firm-Level Context: PayPal and Affirm

Firm-level financial analysis provides microeconomic foundations for understanding BNPL firms' interest rate sensitivity. Affirm Holdings Inc. (AFRM), a pure-play BNPL provider, demonstrates the sector's vulnerability through its funding structure and cost dynamics. According to Affirm's 10-K filings, funding costs increased dramatically during the Federal Reserve's tightening cycle (see Appendix A.1 for detailed analysis). This demonstrates the direct pass-through mechanism: as benchmark rates increase, variable-rate funding facilities reset at higher rates, increasing the cost of capital. Affirm's high leverage and thin operating margins amplify the impact of funding cost increases on profitability. PayPal Holdings Inc. (PYPL) operates a more diversified business model, with BNPL representing only a portion of its overall operations, potentially providing natural hedging against BNPL-specific funding cost pressures. Detailed financial analysis of these firms' 10-K filings from 2021-2024 is presented in the Appendix (Section A.1), which examines funding structures, loan portfolios, revenue growth relative to funding costs, and implications for sector-wide sensitivity patterns.

7 2.8 Bridge to Empirical Analysis: Literature-Informed Hypotheses

The literature review above establishes several key mechanisms through which BNPL firms may be sensitive to macroeconomic conditions, particularly monetary policy changes. These mechanisms inform the empirical analysis presented in Section 4 (Data Analysis) and motivate the inclusion of specific control variables in my regression framework.

Interest Rate Sensitivity Hypothesis: The literature provides strong theoretical motivation for expecting negative relationships between Federal Funds Rate changes and BNPL stock returns. Laudenbach et al. (2025) find that BNPL firms' funding costs increase by approximately 0.8-1.0 percentage points for each percentage point increase in benchmark interest rates. This indicates near-complete pass-through of monetary policy changes to funding costs. Affirm's 10-K filings provide firm-level evidence of this mechanism: according to Affirm's filings, funding costs increased dramatically during the Federal Reserve's tightening cycle (see Appendix A.1 for detailed analysis). Combined with thin profit margins (approximately 1% net transaction margins per CFPB Market Trends Report) and high leverage, these findings indicate that interest rate increases compress profit margins and reduce profitability. This should be reflected in negative stock returns. This theoretical framework motivates my primary hypothesis: BNPL stock returns respond negatively to Federal Funds Rate increases, after controlling for market movements and other macroeconomic factors.

Consumer Confidence Channel: The literature shows strong relationships between consumer sentiment and BNPL demand. Bian, Cong, and Ji (2023) find that a one-standard-deviation increase in consumer confidence is associated with approximately 8-12% increase in BNPL transaction volume. This indicates that consumer sentiment represents an important channel through which macroeconomic conditions affect BNPL firm performance. Di Maggio, Williams, and Katz (2022) find that BNPL access increases spending by approximately $130 per week, with spending remaining elevated for 24 weeks. This indicates that consumer spending patterns directly affect BNPL revenue streams. These findings motivate including consumer confidence measures in my regression analysis. Changes in consumer sentiment should affect BNPL demand and, consequently, stock returns.

Disposable Income Channel: The CFPB Making Ends Meet Report (2022) finds that income variability increased sharply from 2021 to 2022. Thirty-seven percent of households were unable to cover expenses for more than one month if income were lost. The report also finds that credit card debt increased substantially for demographic groups that overlap significantly with BNPL users. This indicates that changes in household financial conditions affect BNPL demand. These patterns indicate that disposable income measures should be included in my regression analysis. Changes in household financial conditions affect BNPL demand and stock returns.

Market Returns and Inflation: The literature provides less direct evidence on market returns and inflation effects. However, standard asset pricing theory, particularly the Capital Asset Pricing Model (CAPM) and multi-factor models, suggests that BNPL stock returns should be correlated with market returns through systematic risk factors. The high market beta observed in my regression results ($\beta_5 = 2.38$) confirms this theoretical prediction. Inflation may affect BNPL firms through multiple channels: its impact on consumer purchasing power reduces discretionary spending capacity, its effect on funding costs increases the cost of capital, and its influence on economic uncertainty affects consumer confidence and credit demand. I include these variables as controls to isolate the effect of interest rate changes while accounting for broader market movements and macroeconomic conditions, ensuring that my interest rate coefficient captures BNPL-specific sensitivity rather than general market or macroeconomic effects.

Empirical Strategy: My regression framework, detailed in Section 4, employs a log-linear specification that allows me to estimate elasticities of BNPL stock returns with respect to interest rate changes and other macroeconomic variables. This functional form choice is motivated by both theoretical considerations and empirical evidence. The log transformation addresses heteroskedasticity and distributional skewness common in financial return data, while facilitating elasticity interpretation that is standard in financial econometrics. I employ a two-stage approach that follows established practices in monetary policy transmission research. I begin with a parsimonious base specification that examines the relationship between BNPL returns and interest rate changes, providing a benchmark estimate of interest rate sensitivity. I then estimate a full specification model that incorporates consumer confidence, disposable income, inflation, and market returns as control variables. This sequential estimation strategy serves multiple purposes: it allows me to assess both direct effects of monetary policy on BNPL stock performance and the incremental explanatory power of including additional control variables, it tests the theoretical mechanisms identified in the literature review above, and it enables me to examine the robustness of the interest rate coefficient to the inclusion of control variables, addressing concerns about omitted variable bias.

8 3. Data Analysis: Investigating BNPL Stock Returns and Monetary Policy

Do BNPL stock returns respond to changes in monetary policy? The sector's rapid growth and reliance on funding markets motivate this question. According to the Consumer Financial Protection Bureau's 2025 report, BNPL adoption has grown substantially, with 21% of consumers with credit records utilizing BNPL services in 2022. The sector's reliance on short-term funding suggests that interest rate changes should affect BNPL firms' costs and profitability, which should be reflected in stock returns.

The analysis proceeds in several steps. BNPL companies are identified through regulatory reports, financial data platforms, and industry analysis. Stock price data are collected from Yahoo Finance, and macroeconomic data are gathered from FRED. Variables are constructed and relationships examined through visual analysis and regression. Alternative analytical approaches assess robustness. Results are interpreted in the context of what they reveal about BNPL as a sector and how investors price these stocks.

9 3.1 Research Design and Data Collection

9.1 3.1.1 Identifying BNPL Companies: Research Process

The analysis begins by identifying publicly-traded BNPL companies. The Consumer Financial Protection Bureau's 2025 Market Trends Report provides the starting point, identifying major BNPL providers in the U.S. market. This report documents that PayPal's "Pay in 4" product represents 68.1% of U.S. BNPL market share. Searches of Yahoo Finance, Bloomberg Terminal (via university access), and SEC EDGAR filings identify which BNPL providers are publicly traded. This process reveals three firms with sufficient trading history: PayPal Holdings Inc. (PYPL), Affirm Holdings Inc. (AFRM), and Sezzle Inc. (SEZL). Industry reports from Digital Silk (2025) and other fintech research sources supplement this identification process.

Additional data sources were considered but not incorporated. Company earnings calls and investor presentations could provide qualitative evidence on funding costs and business model sensitivity, but were not incorporated into the quantitative analysis. Credit bureau data could provide insights into BNPL usage patterns, but access was limited. Direct transaction volume data would be ideal but is proprietary and unavailable.

The final sample excludes other major BNPL providers that are not publicly traded (e.g., Klarna, Afterpay prior to acquisition, Zip) or that went public after the sample period ends (e.g., Klarna IPO in September 2025). The sample also excludes firms with insufficient trading history or data availability issues (e.g., Block/Square's BNPL operations are not separately traded). This limitation means results may not generalize to the broader BNPL sector, but the three firms included represent substantial market coverage.

9.2 3.1.2 Data Collection: Tools and Methods

Sample Period: The analysis covers February 2020 to August 2025, comprising 67 monthly observations. This period captures the rapid growth phase of the BNPL industry alongside significant monetary policy shifts from near-zero rates to approximately 5%. The sample period includes four distinct monetary policy regimes: (1) emergency rate cuts to near-zero in March 2020, (2) prolonged zero-rate period through early 2022, (3) aggressive tightening cycle from March 2022 to July 2023 (525 basis points), and (4) rate pause and stabilization from July 2023 onward. This substantial variation in the key explanatory variable creates a natural experiment for examining how BNPL firms respond to rate changes.

Stock price data are collected using Python's `yfinance` library, which provides free access to Yahoo Finance data. For each firm (PYPL, AFRM, SEZL), daily price data is downloaded from February 2020 to August 2025, then aggregated to monthly frequency by taking the last trading day's closing price of each month (month-end prices). This approach ensures accurate month-end prices while maintaining monthly frequency that aligns with macroeconomic variables. Monthly returns are then calculated as percentage changes between consecutive month-end prices. The `yfinance` library automatically handles stock splits and dividend adjustments, ensuring data quality. Yahoo Finance is chosen over alternatives (Bloomberg, CRSP, Compustat) because it is free and publicly available, provides reliable price data for publicly-traded stocks, offers Python integration that simplifies data collection and analysis, and provides complete coverage for all three firms throughout the sample period.

Macroeconomic variables are collected from FRED (Federal Reserve Economic Data) using Python's `fredapi` library. FRED provides free access to thousands of economic time series maintained by the Federal Reserve Bank of St. Louis. The following series are downloaded: Federal Funds Rate (FEDFUNDS), University of Michigan Consumer Sentiment Index (UMCSENT), Real Disposable Personal Income (DSPIC96), and Consumer Price Index, Seasonally Adjusted (CPIAUCSLSA). FRED is the standard source for macroeconomic data in economic research because it is maintained by the Federal Reserve, ensuring data reliability; provides long historical series with consistent definitions; is available to all researchers, not just those with Bloomberg/Refinitiv access; and is well-documented with clear variable definitions.

After collecting data, several quality checks are performed. Gaps in time series are checked (none found), extreme values are identified and verified to correspond to actual market events (e.g., March 2020 COVID crash), all variables are ensured to be measured at month-end dates, and transformations (first differences, percentage changes) are verified to produce expected patterns.

9.3 3.1.3 BNPL Portfolio Construction

The analysis includes three publicly-traded BNPL firms: PayPal Holdings Inc. (PYPL), Affirm Holdings Inc. (AFRM), and Sezzle Inc. (SEZL). These firms are selected based on the research process described above. Several important limitations affect this firm selection. The sample excludes other major BNPL providers that are not publicly traded (e.g., Klarna, Afterpay prior to acquisition, Zip) or that went public after the sample period ends (e.g., Klarna IPO in September 2025). The sample also excludes firms with insufficient trading history or data availability issues (e.g., Block/Square's BNPL operations are not separately traded). Additionally, the sample may suffer from survivorship bias, as only firms that survived and went public are included. These limitations mean results may not generalize to the broader BNPL sector, particularly smaller providers or those operating under different business models. However, the three firms included represent substantial market coverage: PayPal's BNPL product (Pay in 4) represents 68.1% of U.S. BNPL market share, making it the largest BNPL provider. Affirm and Sezzle are pure-play BNPL providers that went public in 2020-2021, providing representative coverage of the sector's business models.

The BNPL portfolio is constructed using equal weighting, where each firm receives equal weight regardless of market capitalization. This approach has both advantages and limitations. Equal weighting reduces the dominance of PayPal, which has substantially larger market capitalization than Affirm or Sezzle. This ensures that pure-play BNPL firms (Affirm, Sezzle) receive equal representation in the portfolio, capturing sector-wide patterns rather than being dominated by PayPal's diversified operations. Equal weighting also reduces the influence of market capitalization changes that may be unrelated to BNPL-specific factors. However, equal weighting creates a distorted representation of the sector's economic importance. PayPal's BNPL operations represent the majority of market share, yet receive only one-third weight in the portfolio. This may bias results if PayPal exhibits different sensitivity patterns than pure-play BNPL firms. Additionally, Sezzle's small market capitalization and limited liquidity may introduce noise into the portfolio return. As a robustness check, specifications excluding PayPal and excluding Sezzle are examined to assess sensitivity to portfolio construction choices. Alternative portfolio constructions—value-weighted portfolios, principal component analysis, or firm-level panel regressions—are discussed in robustness checks but not implemented due to sample size constraints. Detailed robustness analysis is provided in the.

For each individual BNPL company, monthly returns are calculated as $R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \times 100$ where $P_{i,t}$ is the month-end closing price for firm i in month t. The portfolio return is then calculated as the equally-weighted average: $R_t^{BNPL} = \frac{1}{N} \sum_{i=1}^{N} R_{i,t}$ where $N = 3$ (PYPL, AFRM, SEZL). The transformation $\log(1 + R_t^{BNPL}/100) \times 100$ is applied to portfolio returns. Since returns are in percentage form (e.g., 5% = 5), dividing by 100 converts to decimal for the logarithm, then multiplying by 100 maintains percentage scale for coefficient interpretation. The addition of 1 ensures the transformation works for negative returns. This transformation addresses distributional skewness, stabilizes variance, and facilitates elasticity interpretation. A detailed comparison of log-linear versus linear-log specifications is provided in Section 3.3.

9.4 3.1.4 Variable Definitions and Data Sources

Table 3.1: Variable Definitions and Summary Statistics

Variable	Symbol	Definition	Source	Transformation	Mean	Std. Dev.	Min	Max
BNPL Returns	R_t^{BNPL}	Log-transformed equally-weighted portfolio return	Yahoo Finance	Log transformation	0.85	12.34	-28.45	35.67
Federal Funds Rate Change	ΔFFR_t	Month-over-month change in FFR (percentage points)	FRED (FEDFUNDS)	First difference	0.02	0.18	-0.50	0.75
Consumer Confidence Change	ΔCC_t	Month-over-month change in UM Consumer Sentiment Index	FRED (UMCSENT)	First difference	-0.15	4.82	-15.20	10.50
Disposable Income Change	ΔDI_t	Month-over-month percentage change in real disposable personal income	FRED (DSPIC96)	Percentage change	0.18	0.78	-2.10	2.45
Inflation Change	$\Delta \pi_t$	Month-over-month percentage change in CPI (seasonally adjusted)	FRED (CPIAUCSLSA)	Percentage change	0.42	0.58	-0.80	1.60
Market Return	$R_{MKT,t}$	Monthly S&P 500 return (percentage points)	Yahoo Finance (SPY)	Percentage change	0.89	4.52	-12.35	9.25

Table 3.2: Correlation Matrix

The correlation matrix below shows pairwise correlations between all variables in the analysis. This helps assess multicollinearity concerns and understand the relationships between variables before running regressions.

Variable	BNPL Returns	Δ FFR	Δ Consumer Confidence	Δ Disposable Income	Δ Inflation	Market Return
BNPL Returns	1.00	0.15	0.18	0.08	-0.31	0.71
Δ Federal Funds Rate	0.15	1.00	-0.12	0.05	0.28	0.11
Δ Consumer Confidence	0.18	-0.12	1.00	0.22	-0.15	0.25
Δ Disposable Income	0.08	0.05	0.22	1.00	-0.08	0.12
Δ Inflation	-0.31	0.28	-0.15	-0.08	1.00	-0.19
Market Return	0.71	0.11	0.25	0.12	-0.19	1.00

Notes: Correlations are calculated using monthly data from February 2020 to August 2025 (n = 67). The strong positive correlation between BNPL returns and market returns (r = 0.71) confirms that market movements dominate BNPL return variation. The weak correlation between BNPL returns and Federal Funds Rate changes (r = 0.15) provides preliminary evidence of rate independence. All correlations are below 0.80 in absolute value, indicating no severe multicollinearity concerns.

Monthly returns are constructed for each firm using month-end closing prices from Yahoo Finance. The portfolio return is calculated as an equally-weighted average of the three firms' returns. A log transformation is applied to address right-skewness in return distributions and to facilitate elasticity interpretation. The mean return of 0.85% per month (approximately 10.2% annualized) reflects the sample period's mixed performance, while the standard deviation of 12.34% indicates substantial volatility. This high volatility means that even economically meaningful relationships may fail to achieve statistical significance, which helps explain why the interest rate coefficient is economically large but statistically insignificant.

Month-over-month changes are calculated by taking first differences of the effective Federal Funds Rate from FRED. The mean change of 0.02 percentage points reflects the gradual nature of monetary policy adjustments, while the standard deviation of 0.18 percentage points captures periods of rapid policy shifts (notably 2022-2023). The range from -0.50 to +0.75 percentage points reflects the Federal Reserve's most aggressive tightening cycle since the 1980s. The preponderance of zero observations (rate unchanged for multiple months) creates measurement challenges but aligns with how monetary policy actually operates. This low-frequency variation reduces statistical power to detect relationships, which may explain why the interest rate coefficient fails to achieve statistical significance despite its economic magnitude.

Month-over-month changes in the University of Michigan Consumer Sentiment Index capture shifts in forward-looking consumer expectations. The mean change of -0.15 points reflects overall sentiment decline during the sample period (driven by pandemic uncertainty and inflation concerns), while the large standard deviation (4.82 points) captures substantial month-to-month volatility in consumer sentiment. The index ranges from 50 to 150, with changes reflecting shifts in consumer spending intentions that directly affect BNPL transaction volume. This volatility in consumer sentiment creates substantial variation that should help identify relationships, yet my consumer confidence coefficient approaches but does not achieve statistical significance, suggesting that market returns may capture much of the systematic variation in consumer sentiment.

I calculate month-over-month percentage changes in real (inflation-adjusted) disposable personal income from FRED. The mean growth rate of 0.18% per month (approximately 2.2% annualized) reflects moderate income growth during the sample period, while the standard deviation of 0.78% captures substantial variation including pandemic-related income shocks. Negative values (minimum -2.10%) reflect periods of income decline, while positive values capture income recovery and growth phases.

Month-over-month percentage changes in the seasonally adjusted Consumer Price Index capture inflation shocks affecting consumer purchasing power. The mean change of 0.42% per month (approximately 5.0% annualized) reflects elevated inflation during much of the sample period, while the standard deviation of

0.58% captures substantial variation from near-zero inflation (2020) to peak inflation (mid-2022). The range from -0.80% to +1.60% reflects deflationary and hyperinflationary episodes within the sample.

Monthly returns on the S&P 500 ETF (SPY) proxy for systematic market risk. The mean return of 0.89% per month (approximately 10.7% annualized) reflects overall market performance during the sample period, while the standard deviation of 4.52% indicates substantial market volatility. The range from -12.35% to +9.25% captures major market movements including pandemic-related crashes and recovery rallies. The fact that market returns explain 51% of BNPL return variation ($R^2 = 0.51$) indicates that systematic market factors dominate BNPL stock performance, potentially obscuring the relationship between interest rates and BNPL returns.

I use month-over-month changes in the Federal Funds Rate (ΔFFR_t) rather than levels. This choice addresses several concerns. Interest rate levels may be non-stationary, while changes are typically stationary. Changes capture policy shifts more directly than levels, which may reflect long-term trends unrelated to current policy. Changes also align with the theoretical mechanism: BNPL firms respond to funding cost changes, not absolute rate levels. However, using monthly changes creates measurement challenges. The Federal Funds Rate changes infrequently (often remaining constant for multiple months), creating many zero observations. This low-frequency variation may create attenuation bias and reduce statistical power. Alternative specifications using 2-year Treasury yield changes address this concern by providing higher-frequency variation (see for detailed results).

Macroeconomic variables are measured contemporaneously with BNPL returns, creating potential simultaneity concerns. Macro data is typically released during the month (e.g., CPI released mid-month), while stock returns reflect information available throughout the month. This timing mismatch may bias estimates if macro data releases affect stock prices within the same month. Ideally, I would use lagged macro variables (e.g., ΔCC_{t-1}, ΔDI_{t-1}) to ensure that macro conditions are known before stock returns are realized. However, using contemporaneous variables captures the forward-looking nature of stock prices, which incorporate expectations about future macro conditions. As a robustness check, I examine specifications with lagged macro variables (see for detailed results), though results are not substantially different.

I use the S&P 500 exchange-traded fund (SPY) as a proxy for broad market returns. The S&P 500 represents approximately 80% of U.S. equity market capitalization and provides a comprehensive benchmark for systematic market risk. Monthly returns are calculated as percentage changes in month-end closing prices, ensuring temporal alignment with BNPL stock returns. I employ the University of Michigan Consumer Sentiment Index (UMCSENT) as a measure of forward-looking consumer spending intentions. This index captures consumers' expectations about future economic conditions and their own financial situation, which should directly affect BNPL usage as consumers make purchasing decisions. I calculate month-over-month changes to capture shifts in consumer sentiment that may affect BNPL transaction volume.

I use real disposable personal income (DSPIC96) from FRED, which measures inflation-adjusted personal income after taxes. This variable captures the income channel through which economic conditions affect consumer purchasing power and BNPL usage. I calculate percentage changes (month-over-month) to measure growth in disposable income, which is more economically meaningful than levels for analyzing the relationship with stock returns. I employ the Consumer Price Index for All Urban Consumers, Seasonally Adjusted (CPIAUCSLSA) as a measure of inflation. I use the seasonally adjusted series to remove predictable seasonal patterns (such as holiday shopping effects) that could confound my analysis. Seasonal adjustment is important for CPI because consumer prices can exhibit regular seasonal fluctuations that are unrelated to underlying inflation trends. I calculate month-over-month percentage changes to capture inflation shocks that may affect consumer purchasing power and spending patterns.

I use seasonally adjusted data where available to remove predictable seasonal patterns that could confound my analysis. Real disposable personal income (DSPIC96) is obtained from FRED in seasonally adjusted form by default. Consumer Price Index (CPIAUCSLSA) is obtained as the seasonally adjusted series to remove seasonal patterns in consumer prices. Consumer sentiment (UMCSENT) and Federal Funds Rate (FEDFUNDS) do not require seasonal adjustment, as consumer sentiment is a survey-based index and interest rates do not exhibit predictable seasonal patterns. Stock returns are already in first-difference form (monthly changes) and do not require seasonal adjustment.

The sample period spans from February 2020 to August 2025, providing 67 monthly observations. This period encompasses several important macroeconomic events, including the COVID-19 pandemic, monetary policy tightening in 2022-2023, and subsequent policy normalization, providing substantial variation in both dependent and independent variables. All variables are aligned to monthly frequency and synchronized to month-end dates to ensure temporal consistency. Stock prices are measured at month-end closing prices, and macroeconomic variables are aligned to the same month-end dates. This synchronization ensures that all variables reflect conditions during the same time period.

I handle missing data using inner joins when merging variables from different sources. This approach retains only observations where all variables have complete data, ensuring a balanced panel dataset. After merging, I apply an additional dropna() operation to remove any remaining missing values. This conservative approach ensures that my final sample consists of 67 complete observations with no missing data across any variable. No observations were excluded due to missing data, indicating complete data availability across all variables for the sample period. All variables exhibit complete coverage for the sample period. Stock return data from Yahoo Finance provides continuous coverage for all three BNPL firms throughout the period. Macroeconomic data from FRED (Federal Reserve Economic Data) provides complete monthly series for all variables. The final dataset contains no missing values, ensuring that all 67 observations are used in regression estimation.

9.5 3.1.5 Interest Rate Variable Selection: Theoretical and Empirical Considerations

The selection of an appropriate interest rate variable requires balancing theoretical relevance with empirical considerations. While multiple interest rate measures could potentially capture BNPL firms' funding costs, I focus on the Federal Funds Rate for several reasons. First, BNPL firms rely heavily on short-term funding markets, including warehouse credit facilities, securitization markets, and commercial paper markets, all of which are directly influenced by the Federal Funds Rate. Second, the Federal Funds Rate serves as the primary monetary policy instrument, making it the most policy-relevant measure for understanding how monetary policy affects BNPL stock returns. Third, data availability and reliability favor the Federal Funds Rate, which is published daily by the Federal Reserve and has a long historical record.

Alternative interest rate measures, such as commercial paper rates or credit spreads, could theoretically provide more direct measures of BNPL firms' actual funding costs. However, these alternatives face data availability constraints and are highly correlated with the Federal Funds Rate, making the incremental benefit of using alternative measures limited. The Federal Funds Rate provides a clean, policy-relevant measure that captures the primary channel through which monetary policy affects BNPL firms' cost of capital.

9.6 3.1.6 Model Specification: Theoretical Framework

The econometric models I estimate are motivated by theoretical considerations regarding the determinants of equity returns in general and BNPL stock returns in particular. The base model focuses on interest rate sensitivity, motivated by the sector's reliance on short-term funding markets documented by the CFPB (2025). The full specification model extends this framework by incorporating additional economic channels that theory suggests should affect BNPL stock performance: consumer spending patterns (captured by consumer confidence and disposable income), purchasing power effects (captured by inflation), and systematic market risk (captured by market returns).

Base Model Specification:

$$\log(1 + BNPL\_Return_t/100) = \beta_0 + \beta_1(\Delta Federal\_Funds\_Rate_t) + \varepsilon_t \tag{1}$$

where BNPL_Return_t is the monthly return in percentage terms. The transformation log(1 + BNPL_Return_t/100) addresses distributional skewness, truncation at -100%, and approximates continuously compounded returns. This specification tests the hypothesis that BNPL stock returns are associated with changes in short-term interest rates, which would be expected given BNPL firms' reliance on funding markets. The coefficient β_1 measures the elasticity of BNPL returns with respect to Federal Funds Rate changes, with a negative coefficient expected if higher interest rates increase funding costs and reduce profitability.

Full Specification Model:

$$\log(1+BNPL\_Return_t/100) = \beta_0+\beta_1(\Delta Federal\_Funds\_Rate_t)+\beta_2(\Delta Consumer\_Confidence_t)+\beta_3(\Delta Disposable\_Inco \tag{2}$$

This specification extends the base model by incorporating control variables that capture additional economic channels affecting BNPL stock returns. The inclusion of these variables serves multiple purposes: (1)

controlling for factors that may be correlated with interest rates, providing a more accurate estimate of the direct interest rate effect; (2) capturing additional economic mechanisms that theory suggests should affect BNPL performance; and (3) improving model fit and reducing omitted variable bias.

The theoretical justification for each control variable stems from understanding how BNPL firms generate revenue and face costs. Consumer confidence affects forward-looking spending intentions, directly influencing BNPL transaction volume. Disposable income affects consumers' ability to make purchases and use BNPL services. Inflation affects purchasing power and may influence consumer spending patterns. Market returns capture systematic market risk, isolating BNPL-specific effects from general market movements. Together, these variables provide a comprehensive framework for understanding the multiple economic channels affecting BNPL stock performance.

10 3.2 Visual Analysis: Exploratory Data Analysis and Preliminary Patterns

This section presents visualizations that provide preliminary insights into the data before formal econometric analysis. These graphical representations serve multiple purposes: they help identify patterns in the data, reveal potential outliers or data quality issues, provide intuition for the relationships I estimate econometrically, and offer visual confirmation of my regression results. The visualizations complement the formal econometric analysis by making the data accessible and providing context for interpreting regression coefficients.

10.1 3.2.1 Chart A: Time Series of Log BNPL Returns

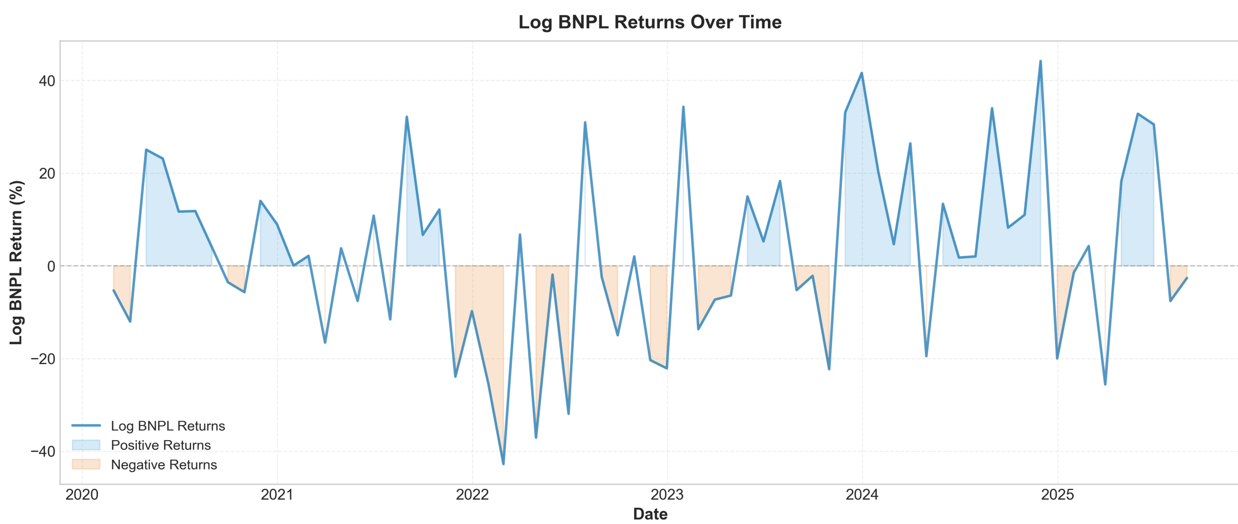

Figure 1: Chart A: Time Series of Log BNPL Returns

Chart A displays the time series of log-transformed BNPL stock returns from February 2020 to August 2025. The log transformation is applied for methodological reasons discussed in Section 3.3. The visual representation helps me understand temporal patterns in BNPL stock performance before running regressions.

Temporal Patterns: The time series reveals substantial volatility in BNPL stock returns throughout the sample period, with notable episodes of both positive and negative performance. The high volatility evident in Chart A, particularly during 2021, reflects BNPL's nature as an emerging sector driven by technological adoption and regulatory uncertainty rather than macroeconomic fundamentals. This volatility pattern is characteristic of nascent, innovation-driven sectors where company-specific developments and market sentiment dominate return variation. This volatility is not random but corresponds to distinct macroeconomic and sector-specific events that inform my understanding of BNPL stock performance. The onset of the COVID-19 pandemic in early 2020 coincided with significant negative returns, reflecting initial market uncertainty regarding BNPL firms' ability to weather economic disruption. Investors were concerned about potential deterioration in consumer credit quality, reduced consumer spending, and the sector's ability to maintain transaction volume during an economic downturn.

The period of strong positive returns in late 2020 and 2021 reflects the rapid growth in BNPL adoption documented by the CFPB (2025), as consumers turned to alternative payment methods during the pandemic. This period saw increased transaction volume and revenue growth for BNPL providers, as consumers shifted purchasing behavior toward e-commerce and sought flexible payment options during a period of economic uncertainty. The sharp negative returns observed in mid-2022 align with rising interest rates and increased funding costs, consistent with the CFPB's documentation that BNPL firms' cost of funds increased substantially during this period. Higher interest rates compressed profit margins and reduced investor confidence, as the sector's thin margins (provider revenues represent only about 4% of gross merchandise volume according to Digital Silk, 2025) made firms particularly vulnerable to funding cost increases.

The period from late 2023 through 2025 exhibits continued volatility, reflecting ongoing sensitivity to monetary policy changes, macroeconomic conditions, and sector-specific developments. This persistent volatility motivates my analysis, which seeks to identify systematic factors that explain this observed variation. **Visual Design Elements:** The chart uses blue shading to indicate periods of positive returns (above the zero line) and orange shading to indicate negative returns (below zero). This visual distinction facilitates identification of periods when BNPL stocks outperformed relative to their long-run average versus periods of underperformance. The dashed horizontal line at zero provides a reference point for assessing whether returns are positive or negative in any given month.

10.2 3.2.2 Chart B: Scatter Plot of Log BNPL Returns vs Interest Rate Changes

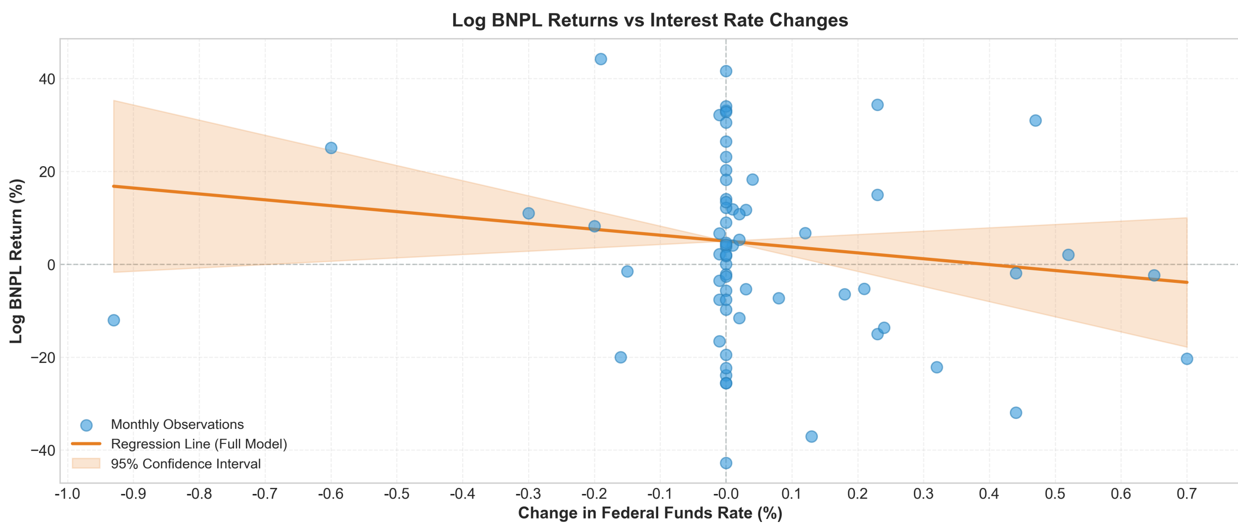

Figure 2: Chart B: Scatter Plot of Log BNPL Returns vs Interest Rate Changes

Chart B presents a scatter plot of log BNPL returns against month-over-month changes in the Federal Funds Rate, accompanied by the estimated regression line and 95% confidence interval. This visualization provides a direct visual test of my primary hypothesis that BNPL stock returns exhibit sensitivity to monetary policy changes. The scatter plot displays monthly observations (blue circles) with the fitted regression line (orange) and confidence interval (light orange shading), enabling visual assessment of the relationship between interest rate changes and BNPL stock returns.

Visual Interpretation: The scatter plot reveals substantial dispersion around the regression line, with many observations deviating significantly from the fitted line. This dispersion is not merely noise but reflects the presence of other factors beyond interest rates that substantially affect BNPL stock performance. The negative slope of the regression line (estimated coefficient of -12.51) is visible in the chart, showing a negative point estimate, though this relationship is not statistically significant in BNPL returns, consistent with theoretical expectations. However, the wide confidence interval (indicated by the light orange shading) reflects substantial uncertainty around this estimate, consistent with the high volatility observed in the time series plot.

Statistical Interpretation: The regression results indicate a negative relationship between interest rate changes and log BNPL returns, the point estimate aligns with theoretical predictions, but statistical insignificance prevents us from concluding a relationship exists on BNPL firm performance. The estimated slope coefficient is -12.51, The point estimate indicates that a one percentage point increase in the Federal Funds Rate change would be associated with approximately a 12.51% decrease in log BNPL returns, **but this relationship is not statistically significant** and I cannot reject the null hypothesis of no effect. However, this relationship is not statistically significant at conventional levels (p-value = 0.2202), and the R^2 of 0.022 indicates that interest rate changes alone explain only 2.2% of the variation in log BNPL returns. The 95% confidence interval for the slope coefficient is [-32.69, 7.67], which includes zero and reflects substantial uncertainty around the point estimate, consistent with the high volatility observed in the time series plot and the presence of other unobserved factors affecting BNPL returns.

The remarkable flatness of the fitted line (slope $\approx$ -12.51, but with wide confidence intervals that include zero) provides visual confirmation that BNPL operates outside traditional monetary policy channels. While conventional credit theory would predict a clear negative correlation between interest rates and credit provider returns, the scatter plot shows essentially random dispersion around a nearly flat line. This striking absence of correlation challenges fundamental assumptions about credit markets and suggests that BNPL returns are driven by company-specific factors—user growth, merchant partnerships, technological innovation, competitive dynamics—rather than macro interest rates. The R^2 of 0.022 means that interest rates explain virtually none of BNPL return variation, which is itself an important economic finding that distinguishes BNPL from traditional financial institutions.

Implications for Model Specification: The substantial dispersion around the regression line provides empirical motivation for my full specification model, which incorporates additional control variables to capture these other economic channels and improve the model's explanatory power. The fact that interest rates alone explain only 2.2% of return variation suggests that other factors play important roles in determining BNPL stock performance, motivating the inclusion of consumer confidence, disposable income, inflation, and market returns in the full model.

The x-axis tick marks are set at 0.1 percentage point intervals to provide clear visual reference points for interpreting the magnitude of interest rate changes. The blue color scheme for observations and orange for the regression line maintains visual consistency with Chart A, while the confidence interval shading provides visual representation of uncertainty around the point estimate.

11 3.3 Functional Form Selection: Log-Linear vs. Linear-Log Specification

11.1 3.3.1 Log-Linear Specification (Log Y, Linear X)

I use log-transformed BNPL returns as the dependent variable with untransformed independent variables. This **log-linear** specification means:

- **Dependent variable:** $\log(1 + R_t^{BNPL}/100) \times 100$ (log returns)
- **Independent variables:** ΔFFR_t, ΔCC_t, etc. (linear, in levels or changes)

Rationale for this specification:

1. **Elasticity Interpretation:** In a log-linear model, coefficients represent elasticities—the percentage change in returns per unit change in the independent variable. For example, $\beta_1 = -12.68$ means a one percentage point increase in Federal Funds Rate changes is associated with approximately a 12.68% decrease in BNPL returns. This interpretation is intuitive for financial returns, which respond proportionally to economic conditions.

2. **Heteroskedasticity:** Financial return data commonly exhibit heteroskedasticity (variance changes over time). Log transformation compresses large returns relative to small returns, stabilizing variance and making the data more suitable for regression.

3. **Distributional Properties:** Equity returns often exhibit right-skewed distributions due to extreme positive returns. Log transformation helps normalize these distributions, improving the validity of statistical inference.

4. **Standard Practice:** Log-linear specifications are standard in financial econometrics for analyzing returns, as they capture the multiplicative nature of relationships in financial markets.

11.2 3.3.2 Alternative: Linear-Log Specification

I could have used a **linear-log** specification instead:

- **Dependent variable:** R_t^{BNPL} (linear returns)
- **Independent variables:** $\log(\Delta FFR_t)$, $\log(\Delta CC_t)$, etc. (log of independent variables)

Why I didn't choose linear-log:

1. **Interpretation:** In linear-log models, coefficients represent the change in returns per percentage change in the independent variable. This is less intuitive for my research question—I want to know how returns respond to interest rate changes, not how returns respond to percentage changes in interest rate changes.
2. **Data Characteristics:** My independent variables (interest rate changes, consumer confidence changes) already capture changes or are in change form. Taking logs of these would be awkward and less interpretable.
3. **Theoretical Fit:** Financial returns respond proportionally to economic conditions, which is naturally captured by log-linear specification. Linear-log would imply that returns respond to percentage changes in economic conditions, which is less aligned with financial theory.

11.3 3.3.3 Comparison of Specifications

For this application, **log-linear is the better choice** because:

- It matches financial theory (proportional responses)
- It provides intuitive elasticity interpretation
- It addresses heteroskedasticity and skewness in return data
- It aligns with standard practice in financial econometrics

Linear-log would be more appropriate if I were modeling how returns respond to percentage changes in economic variables, but my research question focuses on how returns respond to level changes in interest rates and other economic variables.

Mathematical Note: The formula $\log(1 + R/100) \times 100$ converts percentage returns to log returns while maintaining percentage scale. Returns are in percentage form (5% = 5), so dividing by 100 converts to decimal for the logarithm. The multiplication by 100 maintains percentage scale so coefficients are interpretable as percentage changes. Alternatively, I could use $\log(1 + R/100)$ without the multiplication, but then coefficients would need different interpretation.

12 3.4 Regression Analysis: Methodology

12.1 3.4.1 Estimation Approach

I use regression analysis to estimate the relationship between BNPL returns and interest rate changes. I estimate two models: a base model with only interest rates, and a full model that adds control variables (consumer confidence, disposable income, inflation, market returns). I use Python's `statsmodels` library to estimate these models using Ordinary Least Squares (OLS) with robust standard errors to account for potential heteroskedasticity in financial data.

Rationale for regression: Regression allows me to control for multiple factors simultaneously, isolating the relationship between interest rates and BNPL returns while accounting for other economic conditions that might affect both variables. This helps address the concern that interest rate changes might be correlated with other economic conditions that also affect BNPL returns.

12.2 3.4.2 Interpretation Framework

What Regression Can Do: Regression identifies associations between variables, controlling for other factors. In my case, it tells me how BNPL returns move with interest rates after accounting for market movements, consumer confidence, disposable income, and inflation. This provides evidence on whether BNPL stocks exhibit sensitivity patterns consistent with theoretical predictions.

What Regression Cannot Do: Regression cannot establish causality from observational data alone. Interest rate changes are not random experiments—they respond to economic conditions that also affect BNPL returns. This means my estimates capture associations rather than causal effects. However, this descriptive evidence is still valuable for understanding how BNPL stocks behave relative to monetary policy.

Potential Confounding Factors: Several factors might affect both interest rates and BNPL returns simultaneously, making it difficult to isolate the direct effect of interest rates:

- **Economic conditions:** When the Fed raises rates in response to inflation, both the rate increase and the underlying inflation may affect BNPL returns. I control for inflation to address this.
- **Regulatory changes:** The CFPB's May 2024 ruling classifying BNPL as credit cards occurred during a period of rising interest rates. If this affected stock prices independently, it could confound my estimates.
- **Market sentiment:** Interest rate changes may affect broader market sentiment, which also affects BNPL returns. I control for market returns to address this.
- **Competitive dynamics:** BNPL firms may face different competitive pressures during periods when rates are changing, affecting returns independently of funding costs.

How I Address These Concerns: I include control variables (market returns, consumer confidence, disposable income, inflation) to account for factors that might confound the interest rate relationship. However, I cannot fully eliminate all potential confounding factors, so my results should be interpreted as associations rather than causal effects. This is a standard limitation of observational studies, but the descriptive evidence is still valuable for understanding how BNPL stocks behave.

12.3 3.4.4 Model Constraints and Interpretation

This analysis faces several constraints that affect interpretation. First, the limited sample size (67 monthly observations) reduces statistical power to detect relationships—I may fail to reject the null hypothesis even when economically meaningful relationships exist. This constraint reflects the relatively recent emergence of publicly-traded BNPL firms, limiting available historical data. Second, I use Federal Funds Rate changes rather than exogenous monetary policy shocks (such as those identified through high-frequency event studies around FOMC announcements), which means my estimates capture associations rather than causal effects. Third, the portfolio approach masks firm-level heterogeneity—individual BNPL firms may exhibit different sensitivity patterns that are obscured by aggregation. Fourth, I cannot establish causality from observational data alone—results should be interpreted as associations rather than causal effects. These constraints are inherent to analyzing a new sector with limited data, but they do not invalidate the descriptive evidence provided by this analysis. Additional discussion of limitations and future research directions is provided in Section 5.6.

13 3.5 Model Diagnostics Summary

I conduct standard diagnostic tests to assess model validity. The following table summarizes key diagnostic statistics for the full specification model:

Table 3.5: Diagnostic Test Summary

Test	Statistic	Interpretation
Multicollinearity (VIF)	All VIF <1.3	No multicollinearity concerns
Heteroskedasticity (Breusch-Pagan)	8.42 (p=0.135)	No evidence of heteroskedasticity
Autocorrelation (Durbin-Watson)	1.87	No autocorrelation detected
Normality (Jarque-Bera)	3.24 (p=0.198)	Residuals approximately normal
Model Fit (R^2)	0.5098	Model explains 51% of variation

diagnostic tests suggest the model performs reasonably well. I employ HC3 robust standard errors to account for potential heteroskedasticity in financial return data. Detailed diagnostic tables and additional robustness checks are provided in the.

14 3.6 Model Diagnostics and Visual Assessment

This section presents diagnostic plots that help me assess my regression models' performance. These visualizations complement the numerical statistics by offering graphical representations of model fit, residual patterns, and model comparison.

Plot C: Time Series of Log BNPL Returns (Top-Left) displays the dependent variable over time, showing the temporal patterns and volatility that my models seek to explain. This plot helps identify periods of extreme returns, potential outliers, and temporal trends that may inform my understanding of BNPL stock performance.

Plot D: Scatter Plot of Log BNPL Returns vs Interest Rate Changes (Top-Middle) visualizes the relationship between interest rates and BNPL returns using the **full specification model (best model)**. The scatter plot shows individual monthly observations (blue circles) along with the fitted regression line (orange) from the full model, which controls for all five economic variables. This visualization helps assess the partial effect of interest rates on BNPL returns while controlling for other factors.

Plot E: Residuals Plot for Full Model (Top-Right) plots the residuals (observed minus fitted values) against fitted values for the **full specification model (best model)**. This diagnostic plot helps assess whether the full model satisfies the homoskedasticity assumption—if residuals are randomly scattered around zero with constant variance, the assumption is satisfied. Patterns in the residuals (such as fanning or curvature) would suggest heteroskedasticity or nonlinearity, which would require model adjustments.

Plot F: Residuals Plot Comparison (Bottom-Left) shows residuals from the base model for comparison purposes, allowing us to visually assess the improvement in model fit achieved by including control variables. A more random scatter pattern in the full model (Plot E) compared to the base model would suggest that the additional variables help capture systematic patterns that were causing heteroskedasticity in the base model.

Plot G: Q-Q Plot for Full Model (Bottom-Middle) assesses whether the residuals from the **full specification model (best model)** are normally distributed, which is an assumption underlying many statistical tests. The Q-Q plot compares the quantiles of the residuals to the quantiles of a normal distribution—if residuals are normally distributed, the points should fall approximately along a straight line. Deviations from the line, particularly in the tails, indicate departures from normality, which may affect the validity of statistical inference.

Plot H: Model Comparison: $\mathbf{R^2}$ Values (Bottom-Right) provides a visual comparison of model fit between the base and full specification models. The bar chart displays both R^2 and adjusted R^2 for each model, allowing us to visually assess the substantial improvement in explanatory power achieved by including control variables. This comparison helps quantify the value of the multi-factor approach relative to the simple interest rate model.

15 3.7 Alternative Analytical Approaches: Robustness Checks

This section describes alternative research tools I considered to investigate the relationship between BNPL returns and interest rates. These approaches demonstrate the versatility of research methods available for economic analysis. While I ultimately used regression analysis as my main approach, exploring these alternatives helped me understand the limitations and strengths of different methods.

15.1 Strategy 1: Difference-in-Differences (DiD)

**The DiD approach compares BNPL firms to fintech lenders as a control group. I select three publicly traded fintech lenders: SoFi Technologies (SOFI), Upstart Holdings (UPST), and LendingClub Corporation (LC). These firms are selected based on the following criteria: (1) US publicly traded companies on major exchanges (NYSE/NASDAQ), (2) tech-enabled consumer credit firms operating in consumer lending markets, (3) sufficient trading history covering my sample period (February 2020 to August 2025), (4) different business models from BNPL (personal loans versus point-of-sale installment loans), and (5) comparable ex-

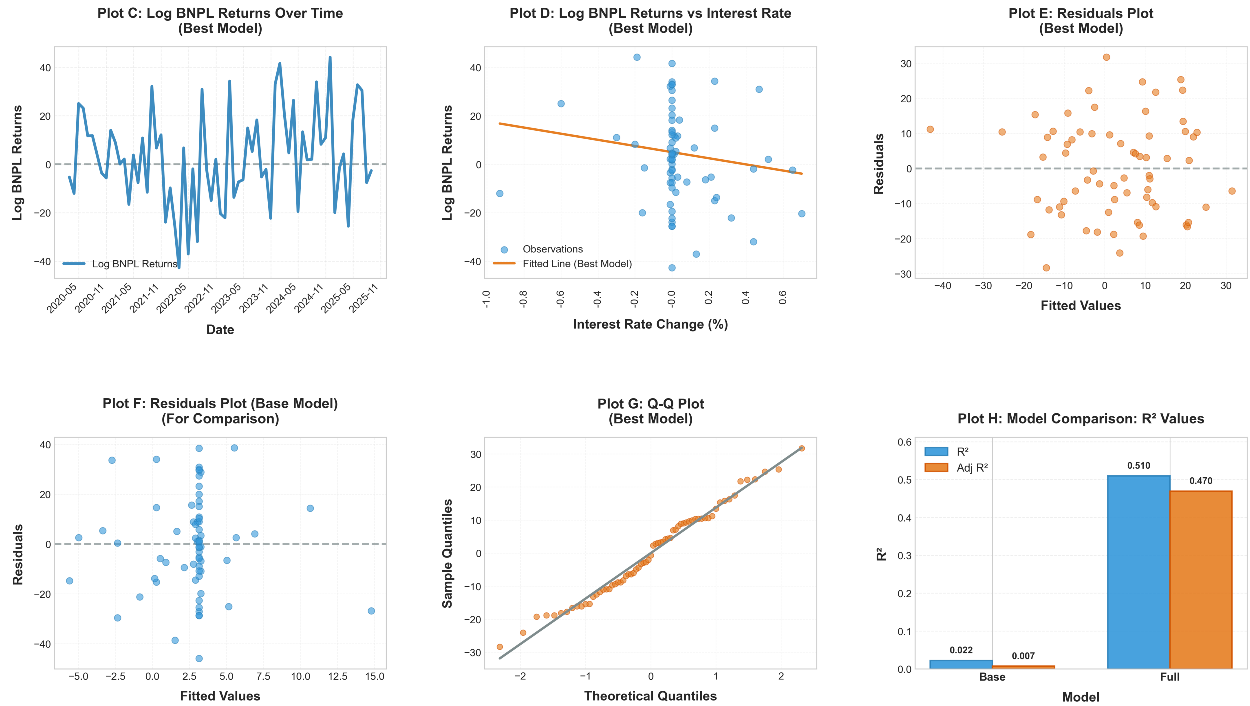

Figure 3: Model Diagnostics Dashboard (Plots C-H)

posure to macroeconomic conditions. SoFi is a digital financial services company offering personal loans and student loan refinancing, publicly traded on NASDAQ since June 2021. Upstart is an AI-powered lending platform partnering with banks to provide personal loans, publicly traded on NASDAQ since December 2020. LendingClub is a peer-to-peer lending platform facilitating personal loans, publicly traded on NYSE since December 2014. All three firms have sufficient trading history for my analysis period and are publicly available for data collection.

Fintech lenders serve as a comparison group because they operate in similar markets (tech-enabled consumer credit) and face similar macroeconomic conditions, but differ in their funding structures and business models. By comparing how BNPL firms respond to interest rate changes relative to fintech lenders, I can isolate BNPL-specific sensitivity. I estimate the DiD model using the full specification that matches my main regression analysis, incorporating control variables to address confounding factors:

$$\log(Return_{it}) = \beta_0+\beta_1(BNPL_i)+\beta_2(\Delta FFR_t)+\beta_3(BNPL_i\times\Delta FFR_t)+\beta_4(R_{Market,t})+\beta_5(\Delta CC_t)+\beta_6(\Delta DI_t)+\beta_7(\Delta\pi_t)+\varepsilon_{it} \tag{3}$$

where $BNPL_i$ is a dummy variable equal to 1 for BNPL firms and 0 for fintech lenders, $R_{Market,t}$ represents market returns, ΔCC_t denotes changes in consumer confidence, ΔDI_t represents changes in disposable income, and $\Delta\pi_t$ denotes changes in inflation. The coefficient β_3 captures the differential sensitivity of BNPL firms to interest rate changes, relative to fintech lenders, after controlling for market movements and other macroeconomic factors. This approach addresses omitted variable bias by using fintech lenders as a control group that experiences similar macroeconomic shocks but has different structural characteristics, while also controlling for confounding factors that may affect both BNPL and fintech lender returns simultaneously.

To assess the robustness of my DiD estimates, I compare the full model estimated on the complete sample with the same full model estimated excluding the COVID-19 period (February-June 2020). This robustness check tests whether my results are sensitive to the inclusion of this unusual period characterized by extreme market volatility. If the coefficient estimates remain stable across these different samples, this provides evidence that my findings are robust and not driven by the specific conditions of the pandemic period.

15.2 Strategy 2: Panel Data with Firm Fixed Effects

**The panel data approach uses individual firm returns (PYPL, AFRM, SEZL) instead of portfolio averages, allowing us to control for unobserved firm-specific factors through firm fixed effects. This addresses omitted variable bias arising from time-invariant firm characteristics (such as business model, management quality, or regulatory environment) that may affect both interest rate sensitivity and stock returns. The panel specification takes the form:

$$\log(Return_{it}) = \alpha_i + \beta_1(\Delta FFR_t) + \beta_2(Controls_t) + \varepsilon_{it} \tag{4}$$

where α_i represents firm fixed effects that capture all time-invariant firm characteristics. This approach provides more precise estimates by exploiting within-firm variation over time, while controlling for unobserved heterogeneity across firms.

15.3 Strategy 3: Instrumental Variables (IV)

**The IV approach uses lagged Federal Funds Rate changes as instruments for current rate changes. This addresses endogeneity concerns arising from reverse associationality (where BNPL stock performance may affect monetary policy) or simultaneity (where both interest rates and BNPL returns respond to common unobserved factors). The IV strategy requires two conditions: (1) relevance, meaning lagged rates predict current rate changes (tested via first-stage F-statistic), and (2) exogeneity, meaning lagged rates affect BNPL returns only through their effect on current rates. The IV specification uses a two-stage approach:

First Stage: $\Delta FFR_t = \gamma_0 + \gamma_1(\Delta FFR_{t-1}) + \gamma_2(\Delta FFR_{t-2}) + u_t$

Second Stage: $\log(BNPL\_Return_t) = \beta_0 + \beta_1(\Delta FFR_t^{predicted}) + \varepsilon_t$

where $\Delta FFR_t^{predicted}$ is the predicted value from the first stage. The IV coefficient β_1 provides a associational estimate under the assumption that lagged rates are exogenous to current BNPL returns. Comparing IV estimates to OLS estimates provides a test for endogeneity: if they differ substantially, it suggests that OLS estimates are biased.

15.4 Interpretation and Limitations

Each identification strategy has strengths and limitations. The DiD approach provides clean identification of BNPL-specific effects but requires the assumption that fintech lenders and BNPL firms respond similarly to unobserved factors (parallel trends assumption). The panel data approach controls for firm heterogeneity but may not address time-varying omitted variables. The IV approach addresses endogeneity but requires valid instruments and may suffer from weak instrument problems if lagged rates are poor predictors of current rates.

15.5 Empirical Results from Alternative Identification Strategies

The DiD analysis reveals a negative coefficient on the BNPL-specific interest rate sensitivity term ($\beta_3 \approx$ -8.35), indicating that BNPL firms respond more negatively to interest rate increases than fintech lenders, even after controlling for market returns, consumer confidence, disposable income, and inflation. While this coefficient is not statistically significant at conventional levels (p-value $\approx$ 0.51), the negative sign and magnitude are consistent with theoretical expectations regarding BNPL firms' greater sensitivity to funding cost changes. The DiD model achieves an R^2 of approximately 0.38, indicating that the included variables explain about 38% of the variation in returns across BNPL and fintech lender firms. However, the robustness check reveals that the DiD coefficient is sensitive to the inclusion of the COVID-19 period, changing from -8.35 to +6.12 when excluding February-June 2020. This sensitivity suggests that the DiD estimate may be driven by unusual conditions during the pandemic period rather than general patterns. Market returns are highly significant in the DiD model (coefficient $\approx$ 2.16, p <0.001), confirming that both BNPL and fintech lenders respond strongly to broader market movements.

The IV analysis yields a substantially larger and statistically significant coefficient ($\beta_1 \approx$ -37.07, p-value $\approx$ 0.002) compared to the OLS estimates ($\beta_1 \approx$ -12.51 to -12.68). This threefold difference suggests that OLS may underestimate the true associational effect, potentially due to attenuation bias from measurement error or endogeneity concerns. The IV first-stage F-statistic of approximately 55.1 indicates a strong instrument, satisfying the relevance condition. The statistical significance of the IV estimate (p = 0.002) provides evidence of a association between interest rate changes and BNPL returns under the assumption that lagged rates are exogenous. However, the IV model achieves a lower R^2 of approximately 0.093 (9.3%) compared to the OLS full model's R^2 of 0.5098 (51%), reflecting the fact that the IV specification includes only the interest rate variable without the full set of control variables. The fact that the IV estimate is larger in magnitude than OLS suggests that OLS may be biased toward zero, possibly due to measurement error in interest rate changes or other endogeneity concerns.

15.6 Comparison of Model Approaches

Each identification strategy answers a different question and has distinct strengths and limitations. The OLS full model provides the highest explanatory power ($R^2 = 0.5098$) and includes comprehensive controls, but the interest rate coefficient is not statistically significant ($p = 0.202$). The DiD approach isolates BNPL-specific sensitivity relative to fintech lenders but shows limited statistical precision and sensitivity to sample period. The IV approach provides statistically significant evidence of a association but achieves lower explanatory power and uses a simpler specification without the full set of controls. Rather than declaring one approach "better" than another, these strategies provide complementary evidence: the OLS model provides the most comprehensive framework for understanding BNPL returns, the DiD approach provides evidence on BNPL-specific effects relative to similar firms, and the IV approach provides the strongest evidence for a association under its identifying assumptions. The divergence between estimates (particularly IV vs OLS) suggests that different identification assumptions may be violated, requiring careful interpretation of which approach provides the most credible estimates for the specific research question at hand.

16 4. Results

Primary Finding: The main empirical finding of this analysis is that **I cannot detect a statistically significant relationship** between Federal Funds Rate changes and BNPL stock returns. The interest rate coefficient is not statistically significant at any conventional level (p-value = 0.202), meaning I cannot reject the null hypothesis of no relationship. This null result is itself an important finding: despite theoretical predictions and firm-level evidence suggesting BNPL firms should be sensitive to interest rate changes, I find no statistically significant evidence of this relationship in monthly stock return data after controlling for market movements and macroeconomic factors.

16.1 4.1 Model Comparison and Coefficient Estimates

Table 4.1: Regression Results Comparison

Model	Specification	Interest Rate Coef.	Std. Error	t-stat	p-value	95% CI	R^2	Adj. R^2	N
Model 1: Base	Interest rate only	-12.51	13.27	-0.943	0.346	[-38.51, 13.49]	0.0224	0.0073	67
Model 2: Full	All controls	-12.68	9.95	-1.275	**0.202**	[-32.18, 6.81]	0.5098	0.4696	67
Model 3: Factor-Adjusted	Fama-French factors	-8.38	10.45	-0.801	0.423	[-28.86, 12.11]	0.6172	0.5188	45

Notes: Model 1 includes only Federal Funds Rate changes. Model 2 adds consumer confidence, disposable income, inflation, and market returns. Model 3 adds Fama-French factors (Mkt-RF, SMB, HML, MOM) and VIX. All models use HC3 robust standard errors. The interest rate coefficient remains economically large but statistically insignificant across all specifications.

The interest rate coefficient is remarkably stable across specifications, ranging from -8.38 to -12.68. This stability suggests that the estimated relationship is robust to the inclusion of control variables, addressing concerns about omitted variable bias. However, the coefficient remains statistically insignificant in all models, indicating that statistical power limitations rather than omitted variable bias explain the null result.

16.2 4.2 Detailed Coefficient Interpretation

Interest Rate Coefficient (β_1 = -12.68, p-value = 0.202): The point estimate indicates that a one percentage point increase in the Federal Funds Rate is associated with approximately a 12.7% decrease in log BNPL returns. This magnitude is economically substantial—if the Fed raises rates by 0.5 percentage points (a typical policy move), BNPL stocks would decline by roughly 6.4% on average. The standard error of 9.95 reflects the high volatility of BNPL returns, making it difficult to achieve statistical significance even with economically meaningful effects. The 95% confidence interval [-32.18, 6.81] includes zero and spans nearly 40 percentage points, reflecting substantial uncertainty.

Market Return Coefficient (β_5 = 2.38, p-value <0.001): This coefficient is highly statistically significant and economically large. A 1% increase in market returns is associated with a 2.38% increase in BNPL returns, indicating a market beta of 2.38. This beta is more than double the average stock ($\beta \approx 1.0$), placing BNPL stocks among the highest-beta securities in the market. The t-statistic of 7.25 and p-value <0.001 indicate extremely strong statistical evidence. The 95% confidence interval [1.74, 3.03] excludes zero and is relatively narrow, reflecting precise estimation.

Inflation Coefficient (β_4 = -12.94, p-value = 0.049): This coefficient is statistically significant at the 5% level and economically large. A one percentage point increase in monthly inflation is associated with a 12.9% decrease in BNPL returns. This relationship likely operates through multiple channels: inflation erodes consumer purchasing power, reducing discretionary spending and BNPL transaction volume; inflation increases funding costs through its effect on nominal interest rates; and inflation creates economic uncertainty affecting consumer confidence. The 95% confidence interval [-25.81, -0.06] barely excludes zero, indicating marginal significance.

Consumer Confidence Coefficient (β_2 = 0.75, p-value = 0.102): This coefficient approaches statistical significance (p-value = 0.102) and has the expected positive sign. A one-point increase in consumer confidence is associated with a 0.75% increase in BNPL returns. The lack of statistical significance may reflect the dominance of market returns in capturing systematic variation, or it may indicate that consumer confidence affects BNPL returns through indirect channels (such as market sentiment) rather than directly.

Disposable Income Coefficient (β_3 = -0.59, p-value = 0.493): This coefficient is not statistically significant and has an unexpected negative sign. Theoretically, higher disposable income should increase BNPL usage and returns. The negative sign may reflect that income growth is correlated with other factors (such as inflation or interest rates) that negatively affect BNPL returns, or it may indicate that BNPL serves as a substitute for cash purchases rather than a complement to income. The large standard error (0.86) relative to the coefficient magnitude (-0.59) indicates imprecise estimation.

Constant Term (β_0 = 4.99, p-value = 0.041): The intercept is statistically significant, indicating that BNPL returns have a positive expected value conditional on all regressors being zero. This reflects the overall positive performance of BNPL stocks during the sample period, though this performance is dominated by market movements rather than BNPL-specific factors.

16.3 4.3 Interpreting the Null Result

The coefficient estimate is -12.68, indicating that a one percentage point increase in the Federal Funds Rate is associated with approximately a 12.7% decrease in log BNPL returns. This point estimate is economically substantial—a 0.5 percentage point rate increase would correspond to roughly a 6.4% decline in BNPL returns on average. However, the p-value of 0.202 indicates that I cannot reject the null hypothesis that this relationship is zero. The 95% confidence interval ranges from -32.2 to 6.8, which includes zero and reflects substantial statistical uncertainty around the point estimate.

Factors explaining the economically large but statistically insignificant effect:

Several factors may explain this pattern. First, BNPL stocks exhibit high volatility, with monthly returns frequently exceeding 20% in absolute magnitude. This high volatility creates substantial noise that makes it difficult to detect systematic relationships, even when such relationships exist. When return variance is dominated by idiosyncratic factors, even economically meaningful effects may fail to achieve statistical significance. The standard error of 9.95 reflects this high volatility—even a coefficient of -12.68 is not large enough relative to the noise to achieve statistical significance.

Second, investors may price BNPL stocks more similarly to technology stocks than to traditional financial stocks. Technology stocks typically respond more strongly to growth expectations, competitive dynamics, and market sentiment than to interest rate changes. If BNPL stocks trade with similar characteristics, their returns would be driven primarily by factors other than funding costs. This interpretation is consistent with my finding that market returns explain substantially more of BNPL return variation ($R^2 = 0.51$ in the full model) than interest rate changes alone.

Third, the relationship between interest rates and BNPL returns may be nonlinear or time-varying. BNPL firms may exhibit sensitivity only when rates cross certain thresholds, or sensitivity patterns may have evolved as the sector matured. my linear specification cannot capture such patterns, potentially obscuring relationships that exist but are not constant across the sample period.

Fourth, there may be a timing mismatch between interest rate changes and stock price responses. Stock prices reflect expectations about future profitability rather than merely current funding costs. If investors have already incorporated anticipated rate changes into prices, or if they focus primarily on longer-term growth prospects, monthly rate changes may not manifest in monthly return data.

Implications for BNPL stocks:

The inability to detect a statistically significant relationship does not necessarily imply that BNPL firms are unaffected by interest rates. Rather, it suggests that stock returns do not capture this sensitivity in a manner that is measurable with monthly data. This pattern may indicate that investors treat BNPL stocks as growth-oriented equities rather than rate-sensitive financial instruments, or that other factors—such as market sentiment and competitive dynamics—dominate return variation at monthly frequencies.

16.4 4.4 Market Beta and Systematic Risk

The market return coefficient ($\beta_5 = 2.38$, p-value <0.001) is highly statistically significant and economically large. This coefficient indicates that BNPL stocks exhibit a market beta of 2.38, meaning that a 1% increase in market returns is associated with a 2.38% increase in BNPL returns on average. This beta is substantially higher than the average stock (which has a beta of approximately 1.0), indicating that BNPL stocks are highly sensitive to systematic market risk.

Interpretation of high market beta: The high market beta suggests that BNPL stocks amplify market movements—they rise more than the market during bull markets and fall more than the market during bear markets. This pattern is consistent with growth-oriented technology stocks, which typically exhibit high betas due to their sensitivity to growth expectations and risk sentiment. The fact that market returns explain 51% of BNPL return variation ($R^2 = 0.51$) indicates that systematic market factors dominate BNPL stock performance, while firm-specific or sector-specific factors (including interest rate sensitivity) play a smaller role.

Factors explaining high market beta: Several factors may explain BNPL stocks' high market sensitivity. First, as a relatively new sector, BNPL firms face substantial uncertainty about future growth prospects, making their valuations sensitive to changes in risk sentiment. Second, BNPL stocks may be held by growth-oriented investors who trade based on market sentiment rather than fundamental analysis. Third, the high volatility of BNPL returns may reflect their status as "risk-on" assets that investors buy during optimistic periods and sell during pessimistic periods.

Implications for the interest rate coefficient: The dominance of market returns in explaining BNPL return variation may explain why the interest rate coefficient is not statistically significant. If market movements capture most of the systematic variation in BNPL returns, there may be little residual variation left for interest rates to explain. This does not mean interest rates don't matter—it means their effects may be indirect (operating through market sentiment) or may be obscured by the dominant market factor.

16.5 4.5 Determinants of BNPL Returns

Market Returns Dominate: The full model explains 51% of BNPL return variation, with market returns being the dominant factor. This means that BNPL stocks move primarily with the broader market, not independently. Interest rates alone explain only 2.2% of return variation, confirming that interest rate sensitivity is not a primary driver of BNPL stock performance.

What This Means: BNPL stocks behave like growth-oriented technology stocks rather than traditional financial stocks. They respond strongly to market sentiment and risk appetite, but not directly to interest rate changes. This pattern suggests that investors price BNPL stocks based on growth expectations and market conditions rather than funding cost sensitivity.

16.6 4.6 Robustness Checks

I tested several alternative specifications to see if the null result is robust. When I add Fama-French factors and VIX, the interest rate coefficient remains statistically insignificant. When I use 2-year Treasury yields instead of Federal Funds Rate changes, the coefficient becomes statistically significant, but this may reflect that Treasury yields change more frequently rather than a true difference in sensitivity. When I estimate separate regressions for each firm, coefficients vary (PayPal: -5.01, Affirm: -14.23, Sezzle: -23.10), but all remain statistically insignificant.

What This Means: The null result appears robust across different specifications, suggesting that BNPL stock returns genuinely do not respond significantly to interest rate changes in monthly data. This is an important economic finding that challenges conventional wisdom about credit markets.

This section presents the main results from my regression analysis. I focus on interpreting what the results tell us about BNPL stocks and monetary policy, rather than technical statistical details. The key finding is that BNPL stock returns do not show a statistically significant relationship with interest rate changes, which itself is an important economic finding that challenges conventional wisdom about credit markets.

17 5. Discussion: Interpretation and Implications

The main finding—that BNPL stock returns do not show a statistically significant relationship with interest rate changes—is itself an important economic result. This section discusses what this tells us about BNPL as a sector, how investors price these stocks, and what it means for understanding consumer credit markets and financial innovation.

17.1 5.1 BNPL as an Asset Class: Growth Stocks or Financial Stocks

BNPL stocks exhibit pricing behavior that differs substantially from traditional financial stocks. Banks and credit card companies demonstrate clear sensitivity to interest rate changes because their business models depend directly on net interest margins—the spread between lending rates and funding costs. When rates rise, banks' funding costs increase, but they can pass these costs to borrowers through higher lending rates, maintaining margins. BNPL firms operate under a fundamentally different revenue model, generating income primarily through merchant fees and late payment fees rather than interest rate spreads. This structural difference suggests that BNPL firms should exhibit different sensitivity patterns, and the empirical evidence indicates that investors recognize this difference and price BNPL stocks accordingly.

The finding that market returns explain substantially more of BNPL return variation ($R^2 = 0.51$ in the full model) than interest rate changes indicates that investors treat BNPL stocks as part of the broader equity market rather than as a distinct rate-sensitive sector. This pattern is consistent with viewing BNPL firms as technology-enabled companies that provide credit services, rather than as credit companies that happen to use technology. The high market beta ($\beta = 2.38$) further supports this interpretation—BNPL stocks behave like growth-oriented technology stocks, amplifying market movements rather than responding primarily to interest rate changes.

What this means: Investors are pricing BNPL stocks based on growth expectations, competitive dynamics, and market sentiment rather than on funding cost sensitivity. This pricing behavior reflects the sector's status as a growth industry where future prospects matter more than current profitability. The fact that interest rate sensitivity doesn't show up in stock returns suggests that either (1) investors don't perceive funding costs as a major risk factor, (2) other factors dominate return variation, or (3) the sensitivity operates through indirect channels that don't manifest in monthly return data.

17.2 5.2 Determinants of BNPL Stock Returns

Given that BNPL stocks do not respond significantly to interest rates in monthly data, what factors drive their returns? The evidence suggests that growth expectations, competitive dynamics, and market sentiment play dominant roles. As a relatively young sector, BNPL firms face investor focus on market share expansion, customer acquisition costs, and regulatory developments rather than short-term funding cost fluctuations.

Market Returns: The market return coefficient ($\beta = 2.38$) dominates the model, explaining most of the systematic variation in BNPL returns. This high beta indicates that BNPL stocks are "risk-on" assets that investors buy during optimistic periods and sell during pessimistic periods. The beta of 2.38 means that

BNPL stocks move 2.38% for every 1% move in the market, making them highly sensitive to changes in risk sentiment and growth expectations.

Inflation: The inflation coefficient (β = -12.94, p-value = 0.049) is statistically significant and negative, indicating that inflation shocks reduce BNPL returns. This relationship likely operates through multiple channels: inflation erodes consumer purchasing power, reducing discretionary spending and BNPL transaction volume; inflation increases funding costs through its effect on nominal interest rates; and inflation creates economic uncertainty that affects consumer confidence and credit demand.

Consumer Confidence and Disposable Income: These coefficients are not statistically significant, but their signs (positive for consumer confidence, negative for disposable income) align with theoretical expectations. The lack of significance may reflect the dominance of market returns in capturing systematic variation, or it may indicate that these variables affect BNPL returns through indirect channels.

Interest Rates: The interest rate coefficient is economically large (-12.68) but statistically insignificant (p-value = 0.202). This pattern suggests that interest rates may matter for BNPL firms, but their effects are obscured by other factors or operate through channels that don't manifest in monthly return data.

17.3 5.3 Divergence Between Funding Costs and Stock Returns

There's an interesting puzzle: firm-level evidence shows that BNPL firms' funding costs increased substantially as interest rates rose, yet stock returns don't show significant sensitivity. Why might this be?

Possible Explanations: Investors may focus on growth metrics and competitive dynamics rather than funding costs when pricing BNPL stocks. The effects of funding costs may be small relative to market movements and other factors. Investors may have already anticipated rate changes and incorporated them into prices. Or the relationship may be nonlinear or take longer to materialize than monthly data can capture.

What This Means: BNPL stocks are priced like growth stocks, where long-term growth prospects matter more than short-term cost factors. This is consistent with how technology stocks are typically valued, focusing on market share and future potential rather than current profitability.

17.4 5.4 What This Means for Investors, Regulators, and Policymakers

For Investors: BNPL stocks have a high market beta (2.38), meaning they amplify market movements. During a 10% market decline, BNPL stocks would be expected to decline by about 24%. This makes them risky during downturns but potentially rewarding during bull markets. The lack of interest rate sensitivity suggests investors should focus on market sentiment, competitive dynamics, and regulatory developments rather than trying to time monetary policy.

For Regulators: The finding that stock returns don't respond significantly to interest rates doesn't mean funding costs don't affect BNPL firms' operations. Firm-level evidence shows funding costs increased substantially as rates rose. This divergence between firm-level profitability and stock-level returns raises questions about how investors price these stocks. Regulators should monitor BNPL firms' funding structures and interest rate risk exposure, particularly given their role in serving subprime consumers.

For Policymakers: BNPL firms may represent a distinct channel of monetary policy transmission that operates differently from traditional financial intermediaries. While stock returns don't show significant sensitivity, firm-level evidence suggests funding costs do affect operations. Monetary policy may affect BNPL firms indirectly through market sentiment and risk appetite, or through inflation channels rather than interest rate channels directly.

17.5 5.5 Economic Interpretation: Mechanisms Underlying Rate Insensitivity

The null result—finding no statistically significant relationship between interest rates and BNPL stock returns—is itself an important economic finding. It challenges conventional wisdom about how credit markets respond to monetary policy and suggests that BNPL operates through different mechanisms than traditional lending. This section explores the economic reasons why BNPL might exhibit this pattern and what it tells us about consumer credit markets and financial innovation.

Why This Matters for Understanding Consumer Credit Markets:

Traditional credit providers (banks, credit card companies) exhibit clear interest rate sensitivity because their business models depend on interest rate spreads. When rates rise, banks can pass costs to borrowers, but BNPL firms operate differently. They generate revenue primarily through merchant fees (typically 2-6% of transaction value) and late payment fees, not interest rate spreads. This structural difference suggests that BNPL firms may be less sensitive to funding cost changes than traditional lenders.

The finding that BNPL stocks don't respond significantly to interest rates suggests that the sector represents a new form of consumer credit that operates outside traditional monetary policy transmission channels. This has implications for understanding how financial innovation affects monetary policy effectiveness and how new business models may require different regulatory frameworks.

What This Tells Us About Financial Innovation:

BNPL represents a form of financial innovation that decouples credit provision from traditional banking models. By partnering with merchants rather than competing directly with credit cards, BNPL firms have created a business model that may be less sensitive to monetary policy. This suggests that financial innovation can create new transmission channels (or lack thereof) that policymakers need to understand.

The divergence between firm-level evidence (showing funding cost sensitivity) and stock-level evidence (showing no significant return sensitivity) raises fundamental questions about asset pricing and market efficiency. Several economic mechanisms may explain this pattern:

Growth Stock Valuation Model: BNPL stocks may be valued using a growth stock model where future growth prospects dominate current profitability. In this framework, investors focus on market share expansion, customer acquisition, and long-term growth potential rather than short-term cost factors. Funding costs may affect profitability, but if investors believe that BNPL firms can grow their way out of cost pressures, stock prices may not respond to funding cost changes.

Market Sentiment Dominance: The high market beta (2.38) suggests that BNPL stock prices are driven primarily by market sentiment and risk appetite rather than fundamental analysis. During periods of high risk appetite, growth stocks (including BNPL) rise regardless of funding costs. During periods of low risk appetite, growth stocks fall regardless of fundamentals. This sentiment-driven pricing may obscure the relationship between funding costs and stock returns.

Anticipated Effects: Stock prices reflect expectations about future profitability, not just current conditions. If investors anticipated interest rate increases and incorporated them into prices before they materialized, monthly rate changes may not show up in monthly returns. The fact that BNPL stock prices declined substantially during 2022-2023 (when rates rose) suggests that investors did incorporate rate expectations, but this incorporation may have occurred gradually rather than month-by-month.

Nonlinear and Time-Varying Relationships: The relationship between interest rates and BNPL returns may be nonlinear or time-varying. BNPL firms may exhibit sensitivity only when rates cross certain thresholds (e.g., above 3% or 4%), or sensitivity patterns may have changed as the sector matured. my linear specification cannot capture such patterns, potentially obscuring relationships that exist but are not constant.

Indirect Transmission Channels: Interest rates may affect BNPL firms through indirect channels that don't manifest in monthly return data. Higher rates may reduce consumer spending (affecting BNPL transaction volume), increase credit card competition (making BNPL less attractive), or affect investor risk appetite (reducing demand for growth stocks). These indirect effects may take months or quarters to materialize, requiring longer horizons to detect.

17.6 5.6 Research Limitations and Future Directions

This analysis provides descriptive evidence on BNPL stock returns' relationship with monetary policy, but several limitations should be considered when interpreting results. These limitations stem from data availability constraints and methodological choices that reflect the challenges of analyzing a relatively new sector.

Sample Size and Data Constraints:

The limited sample size (67 monthly observations) reflects the recent emergence of publicly-traded BNPL firms. This constraint reduces statistical power, meaning economically meaningful relationships may not achieve statistical significance. Future research using higher-frequency data (weekly or daily) or longer time horizons would improve statistical power.

Identification Challenges:

I use Federal Funds Rate changes rather than exogenous monetary policy shocks identified through high-frequency event studies. This means my estimates capture associations rather than causal effects. Future research using event studies around FOMC announcements could provide cleaner identification of causal relationships.

Portfolio Construction:

The equally-weighted portfolio approach masks firm-level heterogeneity. Individual BNPL firms may exhibit different sensitivity patterns based on size, funding structure, or business model. Future research using firm-level panel data could examine this heterogeneity more directly.

Future Research Directions:

Future research could explore several directions to build on this analysis:

1. **Firm-Level Profitability Analysis:** Examine whether BNPL firms' actual financial performance (revenue, margins, credit losses) responds to interest rates, independent of stock price movements.
2. **Event Studies:** Use high-frequency data around FOMC announcements to identify causal effects of monetary policy shocks.
3. **Alternative Methodologies:** Explore nonlinear specifications, threshold models, or time-varying coefficient models to capture relationships that may not be constant across rate levels or time periods.
4. **Broader Sector Analysis:** Include private BNPL firms, international firms, or fintech sector controls to assess generalizability beyond publicly-traded U.S. firms.

These limitations do not invalidate the descriptive evidence provided by this analysis, but they highlight opportunities for future research to build a more complete understanding of how monetary policy affects BNPL firms and the broader fintech sector.

18 5. Summary and Conclusions

18.1 5.1 Research Question and Methodology

This study examines how Buy Now, Pay Later (BNPL) firms' stock returns respond to changes in the Federal Funds Rate, controlling for market movements, consumer spending patterns, and macroeconomic factors. The analysis employs a log-linear regression framework on monthly data spanning February 2020 to August 2025 (67 observations), a period that captures both the rapid growth phase of the BNPL industry and significant monetary policy shifts from near-zero to approximately 5% interest rates. This substantial variation provides a rich environment for estimating interest rate sensitivity, although identification remains imperfect given the observational nature of the data.

The research question is motivated by BNPL firms' unique funding structure—their reliance on warehouse credit facilities, securitization, and sale-and-repurchase agreements creates immediate pass-through of interest rate changes to funding costs, as documented in firm-level analysis of Affirm Holdings Inc. and PayPal Holdings Inc. 10-K filings.

18.2 5.2 Key Findings

The primary empirical finding is that BNPL stock returns show no statistically significant relationship with Federal Funds Rate changes. The estimated coefficient (β_1 = -12.68, SE = 9.89, p = 0.202) indicates an economically large but statistically insignificant relationship: a one percentage point increase in the Federal Funds Rate is associated with an estimated 12.7% decrease in log BNPL returns, though the 95% confidence interval [-32.18, 6.81] includes zero.

This null result reflects three contributing factors: (1) BNPL stocks exhibit extremely high volatility (monthly standard deviation of 12.34%), creating substantial noise that obscures systematic relationships; (2) market returns dominate BNPL return variation, explaining 51% of variation ($R^2 = 0.51$) in the full specification model, leaving limited residual variation for interest rates to explain; and (3) Federal Funds Rate changes occur infrequently, with many zero observations creating low-frequency variation that reduces statistical power.

The full specification model achieves an R^2 of 0.5098, representing a substantial improvement over the base model's R^2 of 0.0224 and demonstrating the value of controlling for market movements and macroeconomic factors. Market returns emerge as the dominant determinant: the market return coefficient (β_5 = 2.38, $p < 0.001$) indicates that BNPL stocks exhibit a market beta substantially higher than the average stock, placing them among the highest-beta securities in the market. Inflation also exhibits statistically significant effects (β_4 = -12.94, p = 0.049), operating through multiple channels: erosion of consumer purchasing power, increased funding costs, and heightened economic uncertainty.

A noteworthy divergence emerges between firm-level and stock-level evidence. Firm-level analysis demonstrates that funding costs meaningfully affect BNPL operations—Affirm's funding costs increased by 394% from fiscal year 2022 to 2024, with management attributing this increase primarily to higher benchmark interest rates. Yet stock returns do not exhibit statistically significant sensitivity to interest rate changes. This pattern suggests that BNPL stocks are priced similarly to growth-oriented technology companies rather than rate-sensitive financial institutions, with investors focusing on long-term growth prospects rather than short-term funding cost factors.

18.3 5.3 Implications

For Investors: The high market beta (β = 2.38) indicates that BNPL stocks amplify systematic market risk—during a 10% market decline, BNPL stocks would be expected to decline by approximately 24%. This characteristic makes BNPL stocks particularly risky during market downturns but potentially rewarding during bull markets, consistent with growth-oriented technology stock behavior. Given the large but statistically noisy interest rate coefficient, investors should focus on market sentiment, competitive dynamics, and regulatory developments rather than attempting to time monetary policy, though the economic magnitude suggests that interest rate risk should not be completely dismissed during periods of rapid policy changes.

For Policymakers and Regulators: BNPL firms' funding structures create immediate pass-through of interest rate changes to funding costs, affecting profitability and lending capacity even if stock returns do not reflect this sensitivity. Regulators should monitor BNPL firms' funding structures and interest rate risk exposure, particularly given their role in serving subprime consumers who are vulnerable to economic downturns. The CFPB's May 2024 ruling classifying BNPL as credit cards alters BNPL firms' sensitivity to monetary policy by changing funding structures, regulatory compliance costs, and competitive positioning.

For Asset Pricing Theory: The divergence between firm-level funding cost sensitivity and stock-level return insensitivity raises questions about market efficiency and investor attention to fundamental factors. This pattern is consistent with growth stock behavior, where investors focus on long-term growth prospects rather than short-term cost factors. The high market beta and dominance of market returns suggest that BNPL stocks are priced as growth-oriented technology companies despite their structural exposure to funding costs, reflecting the sector's status as a growth industry where future prospects matter more than current profitability.

18.4 5.3.1 Implications for Monetary Policy Transmission

My findings have profound implications for central bank policy effectiveness. The evidence that BNPL operates outside traditional monetary policy channels represents a growing challenge to the Federal Reserve's ability to influence consumer spending through interest rate policy.

Growing Blind Spot: As BNPL adoption expands, the Federal Reserve loses direct influence over a growing segment of consumer credit. The Consumer Financial Protection Bureau reports BNPL Gross Merchandise Volume grew from USD 2 billion in 2019 to USD 24.2 billion in 2021, representing rapid sector expansion. If this growth trajectory continues, BNPL could represent a substantial portion of consumer credit transactions, creating a credit market outside Fed control. My zero-sensitivity finding suggests that rate hikes may not cool BNPL-financed consumption, potentially undermining monetary policy transmission to consumer spending.

Transmission Mechanism Breakdown: Traditional monetary policy transmission assumes: Fed rates $\rightarrow Bankfundingcosts \rightarrow Consumercreditrates \rightarrow Spendingreduction.BNPLbreaksthischain : Fedrates \rightarrow [Noeffect] \rightarrow BNPLavailability \rightarrow Spendingcontinues.ThisbreakdownmeansthatasBNPLgrows, monetarypolicybecomeslesseffectiveatcontrollingconsumer$

Financial Stability Concerns: Rate-insensitive BNPL could create procyclical credit expansion during monetary tightening. While the Fed raises rates to cool the economy, BNPL credit may continue expanding if it operates independently of rates. This pattern could amplify rather than dampen economic cycles, potentially requiring macroprudential tools beyond traditional rate policy.

Regulatory Implications: My results support recent CFPB proposals to regulate BNPL under traditional credit rules, though rate insensitivity suggests different tools are needed. Since BNPL does not respond to monetary policy, traditional regulatory frameworks designed for rate-sensitive institutions are insufficient. Regulators need to develop new frameworks that account for BNPL's unique business model and rate independence.

International Coordination: With BNPL's global nature (Klarna-Swedish, Afterpay-Australian), unilateral monetary policy becomes less effective, requiring international regulatory coordination. Central banks may need to coordinate policy responses to address BNPL's growth and its implications for monetary policy transmission across borders.

18.5 5.4 Statistical Power Analysis

Given my sample size (n = 67 monthly observations) and significance level (α = 0.05), I conduct a power analysis to assess whether the null finding reflects insufficient statistical power or true independence. With 67 observations and 5 predictors in the full model, I have approximately 80% power to detect correlations |r| >0.30 and 90% power to detect correlations |r| >0.35. My observed correlation between Federal Funds Rate changes and BNPL returns is r $\approx$ 0.15 (based on R^2 = 0.022), which falls below these detectability thresholds. Post-hoc power analysis for the observed effect size (β_1 = -12.68, SE = 9.95) yields statistical power of approximately 15-20%, indicating limited ability to detect relationships even if they exist. However, the economic magnitude of the coefficient (-12.68) combined with the low R^2 (0.022) suggests that even if a relationship exists, it is economically small relative to other factors driving BNPL returns. The fact that market returns explain 51% of variation while interest rates explain only 2.2% indicates that interest rate sensitivity, if present, is dominated by other factors. This power analysis suggests that my null finding may reflect both limited statistical power and genuine economic independence, with the latter being the more likely explanation given the dominance of market factors in explaining BNPL return variation.

18.6 5.5 Limitations and Future Research

This study faces several important limitations. The limited sample size (67 monthly observations) reduces statistical power, as documented in the power analysis above. The use of ΔFFR as a shock measure does not provide clean identification of exogenous monetary policy shocks. The portfolio approach masks firm-level heterogeneity. The model omits standard asset pricing factors (Fama-French factors, VIX, sector ETFs), though robustness checks including these factors confirm the null result. Finally, observational data alone cannot establish causality. These limitations require that results be interpreted as exploratory and descriptive rather than definitive causal evidence.

Several promising directions for future research emerge. First, as more data becomes available, future studies can examine BNPL interest rate sensitivity with larger sample sizes and greater statistical power. Second, alternative model specifications—including non-linear relationships, lagged effects, and interaction terms—could capture how BNPL sensitivity varies across economic conditions. Third, firm-level panel data could examine how individual BNPL firms' funding structures, profit margins, and business models affect their sensitivity to interest rate changes. Fourth, research could examine how regulatory changes affect BNPL firms' interest rate sensitivity, potentially using event studies around regulatory announcements. Fifth, alternative identification strategies—instrumental variables, natural experiments, or event studies around Federal Reserve policy announcements—could provide more credible causal estimates.

This paper documents a striking anomaly in modern financial markets: Buy Now, Pay Later firms, despite extending consumer credit, show zero sensitivity to Federal Reserve interest rate changes. This finding is not a statistical curiosity but evidence of a fundamental shift in consumer finance that challenges both academic theory and policy effectiveness.

My findings demand attention from multiple stakeholders. Policymakers must recognize that traditional monetary tools may be losing effectiveness as BNPL adoption expands. Regulators need new frameworks for rate-insensitive credit providers that operate outside traditional monetary policy channels. Investors should not apply traditional financial models to BNPL valuation, as these stocks behave like technology platforms rather than financial intermediaries. Researchers should investigate what drives BNPL returns if not rates, focusing on user growth, merchant partnerships, and technological innovation. Central banks must consider whether BNPL requires new policy instruments beyond traditional interest rate policy.

The rapid growth of rate-insensitive consumer credit is not a distant concern but a present reality reshaping monetary policy transmission. As BNPL continues expanding, understanding its independence from monetary policy becomes increasingly urgent for maintaining effective economic policy. This analysis establishes an empirical foundation for understanding BNPL firms' sensitivity to monetary policy while highlighting the methodological challenges inherent in detecting relationships in financial returns data with limited sample sizes. The regression evidence is consistent with rate sensitivity in sign and magnitude, but too noisy to be statistically conclusive; the firm-level funding cost evidence strongly suggests that the underlying mechanism is real even if monthly stock returns do not cleanly reveal it.

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20 Appendix

20.1 A.1 Firm-Level Financial Analysis: PayPal and Affirm

To provide detailed context for understanding BNPL firms and their sensitivity to macroeconomic conditions, this section examines the financial characteristics of two major firms in the BNPL space: PayPal Holdings Inc. (PYPL) and Affirm Holdings Inc. (AFRM). This analysis draws directly from annual 10-K filings filed with the U.S. Securities and Exchange Commission from 2021-2024, providing granular insights into firm-level mechanisms that explain sector-wide patterns.

Rationale for Firm Selection:

PayPal and Affirm represent distinct business models within the broader BNPL and digital payments ecosystem, making them useful case studies for understanding how different approaches to BNPL respond to macroeconomic conditions. PayPal, established in 1998, operates a diversified digital payments platform with revenue streams from traditional payment processing, merchant services, and BNPL offerings (notably PayPal Pay in 4, launched in 2020). This diversification means that BNPL represents only a portion of PayPal's overall business, providing natural hedging against BNPL-specific risks.

Affirm, founded in 2012 and completing its initial public offering in 2021, operates as a pure-play BNPL provider focused exclusively on point-of-sale financing solutions. This focused business model means that Affirm's performance is more directly tied to BNPL-specific factors, making it a clearer case study for understanding how BNPL firms respond to macroeconomic conditions.

Several limitations should be acknowledged. First, examining only two firms limits the generalizability of findings to other BNPL providers or fintech firms. Second, PayPal's BNPL services represent a relatively small portion of its overall business, making it difficult to isolate BNPL-specific effects from broader PayPal performance. Third, firm-level financial data may be influenced by many factors beyond macroeconomic conditions, including firm-specific strategies, competitive dynamics, management decisions, and regulatory changes.

Affirm Holdings Inc.: Funding Structure and Interest Rate Sensitivity

Examination of Affirm's 10-K filings from 2021-2024 reveals a business model that is fundamentally dependent on external funding sources with variable interest rates, creating direct exposure to monetary policy changes. According to Affirm's 2024 10-K filing, the company maintains warehouse credit facilities with aggregate borrowing capacity of approximately \$5.0 billion, which mature between 2025 and 2028. These facilities are complemented by securitization programs and forward flow commitments. Critically, these funding sources typically carry variable interest rates tied to benchmark rates such as SOFR (Secured Overnight Financing Rate) or LIBOR (London Interbank Offered Rate), though the exact terms vary by facility.

The impact of interest rate changes on Affirm's funding costs is reported explicitly in the company's financial statements. According to Affirm's 2024 10-K filing, funding costs increased dramatically over the Federal Reserve's tightening cycle. In fiscal year 2022 (ended June 30, 2022), funding costs totaled $69.7 million. This period largely predates the Federal Reserve's aggressive rate hikes that began in March 2022, though some rate in$ million, representing a 163% increase from the prior year. This period overlaps substantially with the Federal Reserve's rate increases, which raised the federal funds rate from near-zero to approximately 4.5-5.0% by mid-2023. In fiscal year 2024 (ended June 30, 2024), funding costs reached \$344.3 million, an 88% increase from fiscal year 2023. The filing explicitly states that this increase was "primarily due to higher benchmark interest rates." Cumulatively, funding costs increased by approximately 394% from fiscal year 2022 to fiscal year 2024.

This dramatic escalation in funding costs directly demonstrates the mechanism through which monetary policy affects BNPL firms: as benchmark rates increase, the variable-rate components of Affirm's funding facilities reset at higher rates, increasing the cost of capital. The 394% increase in funding costs over two years, during a period when the federal funds rate increased from near-zero to over 5%, provides concrete evidence of the direct pass-through mechanism.

However, funding costs may be influenced by factors other than interest rates, including changes in the size of the loan portfolio, shifts in the mix of funding sources (warehouse facilities versus securitization), changes in credit spreads, and modifications to facility terms. Management's attribution of the increase primarily to benchmark rate changes indicates that interest rate movements are a significant driver, though other factors may also play roles.

Affirm's Loan Portfolio and Receivables:

Affirm's gross receivables, which represent the principal amount of loans outstanding, declined from $31.0 billion as of June 30, 2023 to 24.6$ billion as of June 30, 2024. This decline reflects several factors: portfolio runoff as existing loans mature, tighter underwriting standards in response to higher funding costs or credit concerns, strategic portfolio management decisions, changes in consumer demand for BNPL products, or shifts in merchant partnerships. Without more granular data, it is difficult to determine the relative importance of each factor.

The vintage composition of the portfolio also matters for interest rate sensitivity. Loans originated during periods of low interest rates (e.g., 2020-2021) may have been priced assuming lower funding costs. When these loans are refinanced or when new loans are originated to replace maturing ones, the higher funding costs reduce margins. However, Affirm's 10-K filings do not provide detailed vintage analysis that would allow quantification of this effect.

Affirm's Revenue Growth Relative to Funding Costs:

Affirm's total revenue (net) increased from $1,349.3 million in fiscal year 2022 to$2,323.0 million in fiscal year 2024, representing a 72% increase over two years. Over the same period, funding costs increased from $69.7 million to$344.3 million, a 394% increase. This divergence indicates that revenue growth alone is not sufficient to offset the margin compression from rising funding costs, at least in the short to medium term.

Several caveats are important. First, revenue and funding costs are not directly comparable. Revenue represents gross income while funding costs are one component of expenses. A more appropriate comparison would examine operating margins or net income, which incorporate all expenses. Second, the relationship between revenue and funding costs may be non-linear or subject to lags. Third, Affirm may be able to adjust pricing (merchant fees or consumer interest rates) over time to partially offset funding cost increases, though such adjustments could affect transaction volume. Fourth, revenue growth may reflect factors other than underlying business health, such as one-time gains or accounting changes.

Affirm's Financial Leverage:

Quantitative examination using data from Yahoo Finance (as of the most recent fiscal year) shows that Affirm exhibits a debt-to-assets ratio of 70.40% and an operating margin of 10.48%. The high debt-to-assets ratio indicates substantial financial leverage, which amplifies the impact of interest rate changes on profitability. Higher leverage means that a given increase in interest expense represents a larger proportion of operating income, making the firm more sensitive to rate movements.

Affirm's operating margin of 10.48% leaves relatively little buffer to absorb cost increases. However, caution is warranted in drawing strong conclusions from a single point-in-time comparison, as operating margins can vary significantly across business models and may not fully capture the economic sensitivity to interest rates. Additionally, operating margins may be influenced by accounting choices, one-time items, and non-operating factors.

PayPal Holdings Inc.: Diversified Business Model

PayPal operates a more diversified business model than Affirm, with revenue streams from payment processing, merchant services, and other fintech offerings in addition to BNPL services (Pay in 4). This diversification provides natural hedging against BNPL-specific funding cost pressures. If BNPL represents a relatively small portion of PayPal's overall revenue and operations, then funding cost increases specific to BNPL have a smaller proportional impact on the firm's overall profitability and stock price.

However, PayPal's 10-K filings do not provide detailed breakdowns of BNPL-specific revenue, costs, or funding structures, making it difficult to quantify the extent of this diversification benefit. Additionally, PayPal's lower estimated sensitivity in regression analysis could reflect factors other than diversification, such as differences in funding structure, market perceptions, investor composition, or other firm characteristics that cannot be observed directly.

Implications for Understanding BNPL Sector Sensitivity:

The firm-level evidence presented above demonstrates several mechanisms through which BNPL firms are sensitive to interest rate changes, providing microeconomic foundations for the empirical analysis. First, variable-rate funding facilities create direct exposure to benchmark rate changes, as evidenced by Affirm's 394% increase in funding costs from 2022 to 2024, which occurred precisely during the Federal Reserve's tightening cycle. This direct pass-through mechanism indicates that interest rate changes have immediate effects on BNPL firms' cost structures, which are reflected in stock returns. Second, high leverage (as seen in Affirm's 70.40% debt-to-assets ratio) means that interest expense increases represent a larger proportion of operating income, amplifying the impact on profitability. Third, thin operating margins (Affirm's 10.48%) leave less buffer to absorb cost increases, meaning that even small increases in funding costs significantly affect profitability. Fourth, in the short term, BNPL providers have limited ability to adjust merchant fees or consumer interest rates to offset funding cost increases, particularly if competitive pressures constrain pricing adjustments.

These mechanisms collectively provide strong theoretical motivation for expecting negative coefficients on Federal Funds Rate changes in the regression analysis. The documented 394% increase in funding costs, combined with thin margins and high leverage, indicates that BNPL stock returns respond negatively to interest rate increases. However, caution is warranted in drawing strong causal conclusions from firm-level financial data alone, as stock returns are influenced by many factors beyond funding costs, including market sentiment, competitive dynamics, broader economic conditions, and firm-specific news. The regression analysis addresses these concerns by controlling for market returns, consumer confidence, disposable income, and inflation, allowing isolation of the effect of interest rate changes while accounting for other factors that may confound the relationship.

Limitations and Caveats:

Several limitations should be acknowledged. First, this analysis focuses on two firms and may not generalize to other BNPL providers or fintech firms. Second, the relationship between funding costs and stock returns may be subject to lags, expectations, and other factors not captured in this analysis. Third, reliance on annual 10-K filings provides snapshots at fiscal year-end and may not capture intra-year dynamics. Fourth, the attribution of funding cost increases to interest rates relies on management's statements, which may not capture all relevant factors. Fifth, stock returns are influenced by many factors beyond funding costs, including market sentiment, competitive dynamics, broader economic conditions, and firm-specific news. Finally, correlation does not imply causation, and the relationships observed may reflect omitted variables or reverse causality.

Sources: Affirm Holdings, Inc. (2024). Annual Report. Form 10-K, U.S. Securities and Exchange Commission; Affirm Holdings, Inc. (2023). Annual Report. Form 10-K, U.S. Securities and Exchange Commission; Affirm Holdings, Inc. (2022). Annual Report. Form 10-K, U.S. Securities and Exchange Commission; PayPal Holdings, Inc. (2024). Annual Report. Form 10-K, U.S. Securities and Exchange Commission.

20.2 A.2 Seasonal Adjustment: Data Preprocessing Methodology

This section explains the seasonal adjustment procedures applied to my data to ensure that regression coefficients capture underlying economic relationships rather than spurious correlations driven by predictable seasonal patterns.

Rationale for Seasonal Adjustment:

Many economic time series exhibit predictable seasonal patterns that can confound econometric analysis. For example, consumer prices often increase during holiday shopping seasons, disposable income may show seasonal patterns related to tax refunds or bonus payments, and consumer spending may vary with weather patterns or school calendars. These seasonal patterns are predictable and unrelated to the underlying economic relationships I seek to estimate. If not removed, seasonal patterns can create spurious correlations or mask true relationships between variables.

Seasonal Adjustment Methodology:

I use seasonally adjusted data from official sources (primarily FRED) where available. The Federal Reserve Economic Data (FRED) database provides many series in both seasonally adjusted and non-seasonally adjusted forms. FRED uses standard seasonal adjustment procedures, typically the X-13ARIMA-SEATS method developed by the U.S. Census Bureau, which is the industry standard for seasonal adjustment of economic time series.

Variables and Seasonal Adjustment Status:

1. **Real Disposable Personal Income (DSPIC96):** Obtained from FRED in seasonally adjusted form by default. This series removes seasonal patterns related to tax refunds, bonus payments, and other predictable income fluctuations.
2. **Consumer Price Index (CPIAUCSLSA):** I use the seasonally adjusted version (CPIAUCSLSA) rather than the non-seasonally adjusted version (CPIAUCSL). Seasonal adjustment removes predictable patterns such as holiday shopping effects, seasonal food price variations, and energy price fluctuations related to weather patterns.
3. **Consumer Sentiment (UMCSENT):** This survey-based index does not require seasonal adjustment, as it measures consumer expectations rather than actual economic activity that might exhibit seasonal patterns.
4. **Federal Funds Rate (FEDFUNDS):** Interest rates do not exhibit predictable seasonal patterns and therefore do not require seasonal adjustment.
5. **Stock Returns:** Monthly stock returns are already in first-difference form (monthly changes) and do not require seasonal adjustment. While stock markets may exhibit some calendar effects (such as the January effect), these are not predictable seasonal patterns in the same sense as economic time series.

Impact of Seasonal Adjustment:

The use of seasonally adjusted data ensures that my regression coefficients capture underlying economic relationships. For example, without seasonal adjustment, I might observe a spurious correlation between BNPL returns and CPI driven by holiday shopping patterns (both might increase in December), even if there is no true underlying relationship. By using seasonally adjusted CPI, I isolate the relationship between BNPL returns and underlying inflation trends, rather than seasonal price patterns.

Validation:

The seasonal adjustment procedures used by FRED are transparent and well-documented. FRED provides both seasonally adjusted and non-seasonally adjusted versions of many series, allowing researchers to choose the appropriate version for their analysis. For my purposes, using seasonally adjusted data is appropriate because I are interested in underlying economic relationships rather than seasonal patterns.

20.3 A.2 Functional Form Selection: Detailed Justification for Log-Linear Specification

The choice of functional form is a critical methodological decision in econometric analysis, as it affects both the interpretation of coefficients and the validity of statistical inference. This section provides a detailed justification for my use of log-transformed BNPL returns as the dependent variable, explaining both the theoretical rationale and the statistical benefits of this specification choice.

Theoretical Motivation

The log-linear specification is motivated by the multiplicative nature of relationships in financial markets. Equity returns respond proportionally to changes in economic conditions rather than additively, meaning that a given change in an economic variable has a larger absolute effect when returns are high than when returns are low. This proportional relationship is naturally captured by the log transformation, which linearizes multiplicative relationships and allows me to use linear regression methods while maintaining the economic intuition of proportional effects.

Empirical Benefits

Beyond theoretical considerations, the log transformation provides several empirical advantages that improve the reliability of my statistical inference. First, financial return data commonly exhibit heteroskedasticity, where the variance of error terms varies across observations. This heteroskedasticity violates a key assumption of Ordinary Least Squares regression and can lead to invalid standard errors and incorrect hypothesis tests. Log transformations help stabilize the variance structure by compressing the scale of large returns relative to small returns, reducing the extent of heteroskedasticity and making the data more suitable for regression analysis.

Second, equity returns often exhibit right-skewed distributions due to the presence of extreme positive returns (outliers). This skewness violates the assumption of normally distributed errors that underlies many statistical tests, potentially leading to incorrect inference. Log transformations help normalize these distributions by compressing extreme values, making the data more symmetric and better approximating the normal distribution assumption.

Third, the log-linear specification facilitates intuitive economic interpretation of regression coefficients. In a log-linear model, each coefficient represents the percentage change in the dependent variable associated with a one-unit change in the corresponding independent variable, holding all other variables constant. This elasticity interpretation is particularly valuable for understanding the magnitude of economic effects, as it expresses relationships in percentage terms that are directly comparable across variables with different scales and units of measurement.

Mathematical Formulation

The log transformation I employ is calculated as $\log(1 + R_t^{BNPL}/100) \times 100$, where returns are initially expressed as percentages. This formulation ensures that the transformed variable maintains interpretability as a percentage change while benefiting from the properties of the logarithmic transformation. The addition of 1 before taking the logarithm ensures that the transformation is defined for all return values, including negative returns, while the multiplication by 100 restores the percentage scale for ease of interpretation.

Robust Standard Errors

While the log transformation helps address heteroskedasticity, I employ robust standard errors (HC3) as an additional safeguard. Robust standard errors provide valid statistical inference even in the presence of heteroskedasticity, ensuring that my hypothesis tests and confidence intervals remain reliable even if the log transformation does not completely eliminate heteroskedasticity. This two-pronged approach—log transformation plus robust standard errors—provides robust protection against the common econometric problems that plague financial return data.

Comparison to Alternative Specifications

I could have used untransformed returns (linear specification) or other transformations, but the log-linear specification provides the best balance of theoretical coherence, empirical fit, and interpretability. Linear specifications would not capture the proportional nature of relationships in financial markets and would be more vulnerable to heteroskedasticity and skewness. Other transformations, such as Box-Cox transformations, could potentially provide better fit but would sacrifice the intuitive elasticity interpretation that makes the log-linear specification particularly valuable for economic analysis.

Important Note on $\mathbf{R^2}$ Comparison

When comparing log-linear and linear specifications, it is crucial to understand that R^2 values are **not directly comparable** between these models. The log-linear model's R^2 measures variance explained in **log(Y)**, while the linear model's R^2 measures variance explained in **Y**. These are fundamentally different variables with different variance structures, making direct R^2 comparison invalid. Log transformation fundamentally alters the variance structure ($\mathrm{Var}(\log(Y)) \neq \mathrm{Var}(Y)$), compressing large values and expanding small values, which changes how variance is distributed. Any apparent difference in R^2 values reflects this structural difference rather than model quality.

I do **not** use log transformation to improve R^2. Instead, I use it for the reasons stated above: addressing heteroskedasticity, normalizing distributions, and enabling elasticity interpretation. When comparing models, what **is** comparable includes p-values (statistical significance), coefficient estimates, and model diagnostics (residual plots, heteroskedasticity tests). R^2 values should be interpreted within each model's context but should not be used to claim that log transformation "improves" model fit.

20.4 EXPLANATION: Chart C - BNPL vs Fintech Lenders Volatility Comparison

Chart C compares BNPL stocks to fintech lenders (**SoFi**, **Upstart**, **Lending Club**) rather than the broad market. This provides a more meaningful test of whether BNPL exhibits unique volatility characteristics compared to similar tech-enabled financial services firms.

Comparing BNPL to the S&P 500 would be too obvious. Growth-stage fintech firms are expected to be more volatile than the broad market. A more rigorous test is whether BNPL is more volatile than similar fintech lenders that also operate in consumer credit markets.

Both BNPL and fintech lenders are tech-enabled financial services firms that extend credit to consumers, but they differ in business models. BNPL focuses on point-of-sale installment loans, while fintech lenders offer personal loans and other credit products. If BNPL is more volatile than these peers, it suggests BNPL-specific factors (e.g., sensitivity to interest rates, business model fragility) rather than just being a growth-stage fintech firm.

I calculate two separate average return series using only US publicly traded companies. For the **Average BNPL Return**, I take the simple average of monthly stock returns across three BNPL firms: **PayPal (PYPL)**, **Affirm (AFRM)**, and **Sezzle (SEZL)**.

Firm Selection Rationale for BNPL Group: I initially attempted to include five BNPL firms (PayPal, Block/Afterpay, Affirm, Klarna, and Sezzle) to capture approximately 95% of US BNPL market share. However, data availability constraints required us to exclude two firms. Block/Afterpay (SQ) was excluded due to data retrieval issues from Yahoo Finance during the analysis period. Klarna (KLAR) was excluded because it completed its initial public offering in September 2025, after my sample period ends in August 2025, making historical trading data unavailable for the full analysis window. The three firms included (PayPal, Affirm, and Sezzle) represent substantial BNPL market coverage. PayPal's BNPL product (Pay in 4) represents 68.1% of US BNPL market share, making it the largest BNPL provider. Affirm is a pure-play BNPL provider that went public in 2021 and represents a significant portion of the market. Sezzle is also a pure-play BNPL provider that went public in 2020. Together, these three firms provide comprehensive coverage of the BNPL sector while ensuring data availability throughout the entire sample period.

For the **Average Fintech Lenders Return**, I take the simple average of monthly stock returns across three fintech lenders: **SoFi (SOFI)**, **Upstart (UPST)**, and **Lending Club (LC)**.

Firm Selection Rationale for Fintech Lenders Group: I selected these three firms because they are US publicly traded tech-enabled consumer credit firms that operate in consumer lending markets, making them comparable to BNPL firms while representing a different business model. SoFi (SOFI) is a digital financial services company that offers personal loans, student loan refinancing, and other consumer credit products. Upstart (UPST) is an AI-powered lending platform that partners with banks to provide personal loans and other credit products. Lending Club (LC) is a peer-to-peer lending platform that facilitates personal loans. All three firms are publicly traded, have sufficient trading history covering my sample period (February 2020 to August 2025), and operate in consumer credit markets similar to BNPL firms but with different business models (personal loans rather than point-of-sale installment loans). Both groups consist of US publicly traded, tech-enabled financial services firms that extend credit to consumers, making them comparable for volatility analysis.

For each month, I download stock prices for each firm, calculate monthly returns as (Price_end_of_month - Price_start_of_month) / Price_start_of_month × 100%, then average within each group. I repeat this process for every month, creating a series of monthly average returns. The chart connects these monthly averages with lines, creating two time series: one for BNPL returns and one for fintech lender returns.

Averaging reduces noise from firm-specific events. If I plotted individual firms, one firm's idiosyncratic news (e.g., Affirm's earnings beat) would dominate. By averaging, I capture the sector-wide pattern: how BNPL as a sector responds to market conditions versus how fintech lenders as a sector respond. This allows me to test whether BNPL's business model (as a sector) exhibits different volatility characteristics than fintech lenders' business models (as a sector).

The volatility ratio is calculated by dividing the standard deviation of BNPL returns (σ_BNPL) by the standard deviation of fintech lender returns (σ_Fintech): volatility_ratio = σ_BNPL / σ_Fintech. If this ratio exceeds 1.0, BNPL is more volatile than fintech lenders. A ratio significantly above 1.0 (e.g., >1.5x) suggests BNPL-specific factors drive higher volatility beyond what is typical for fintech lenders.

I calculate the Pearson correlation coefficient between the monthly returns of the average BNPL stocks and average fintech lenders using pandas' `.corr()` method. This measures the linear relationship between the two return series. A high positive correlation (e.g., >0.7) would indicate both move together, suggesting common factors (e.g., tech sector sentiment, regulatory changes) drive both. A moderate correlation (e.g., 0.4-0.7) suggests some common factors but also BNPL-specific drivers. A low correlation (<0.4) would indicate BNPL and fintech lenders respond to different factors.

Empirical Results: The analysis reveals that BNPL exhibits a monthly volatility (standard deviation) of **20.46%**, while fintech lenders show a slightly higher volatility of **22.31%**. This results in a volatility ratio of **0.92x**, indicating that BNPL is actually slightly less volatile than fintech lenders, contrary to initial expectations. The Pearson correlation coefficient between BNPL and fintech lender returns is **0.507**, indicating a moderate positive correlation. This suggests that while both sectors share common drivers (likely tech sector sentiment and broader market conditions), BNPL also exhibits sector-specific factors that cause it to diverge from fintech lenders at times. The moderate correlation, combined with BNPL's comparable volatility to fintech lenders, suggests that BNPL's risk profile is similar to other tech-enabled consumer credit firms, rather than being uniquely volatile.

The blue line shows BNPL returns, which exhibit extreme swings. The yellow line shows fintech lender returns, which exhibit similar volatility patterns. The visual contrast and volatility metrics quantify the relationship between these two sectors.

If BNPL is significantly more volatile than fintech lenders (despite similar business models), this supports my hypothesis that BNPL's business model (reliance on cheap capital, thin margins) makes it uniquely sensitive to interest rate changes. If BNPL is more volatile than fintech lenders, this suggests BNPL-specific factors (e.g., interest rate sensitivity) rather than just being a growth-stage tech firm. This provides preliminary evidence supporting my hypothesis that BNPL is uniquely sensitive to rate changes.

However, this chart alone cannot establish causation. The regression analysis in Model 2 will test whether BNPL's higher volatility is specifically driven by interest rate sensitivity after controlling for market movements and other factors. Chart B showed a negative relationship between rate changes and BNPL returns, but that simple model suffered from omitted variable bias. Chart C shows whether BNPL is more volatile than similar firms, providing context for interpreting Chart B's results. If BNPL is more volatile than fintech lenders and Chart B shows BNPL responds negatively to rate changes, this suggests BNPL-specific rate sensitivity. Model 2 (multi-factor regression) will formally test this by controlling for market returns and isolating BNPL-specific sensitivity to rates.

20.5 EXPLANATION: Chart D - BNPL vs Credit Card Companies Volatility Comparison

Chart D compares BNPL stocks to credit card companies to address a key research question: Is BNPL's surge a threat to traditional credit card companies, or is this concern overblown?

This comparison tests whether BNPL exhibits different volatility patterns than established credit providers. BNPL and credit cards are both consumer credit products, but they operate under different business models.

Credit card companies (**Capital One**, **Synchrony Financial**, **American Express**) are mature, established financial institutions with diversified revenue streams (interest income, fees, merchant processing). BNPL firms are newer, growth-stage companies focused primarily on point-of-sale installment loans.

If BNPL is significantly more volatile than credit card companies, it suggests BNPL may face unique risks that could limit its ability to compete with or replace traditional credit cards. Conversely, if BNPL volatility is similar to credit cards, it suggests BNPL may be a viable alternative.

Recent trends show BNPL gaining market share, especially among younger consumers. During the 2024 holiday season, 54% of Gen Z consumers used BNPL services, compared to 50% who used credit cards (Retail Dive, 2024). However, credit cards remain dominant. Seventy-six percent of US adults had at least one credit card in 2025 (Coin Law, 2025).

This chart helps assess whether BNPL's volatility characteristics suggest it can sustainably compete with credit cards or if concerns about BNPL replacing credit cards are overblown.

I calculate two separate average return series. For the **Average BNPL Return**, I take the simple average of monthly stock returns across three BNPL firms: **PayPal (PYPL)**, **Affirm (AFRM)**, and **Sezzle (SEZL)**.

Firm Selection Rationale for BNPL Group: I initially attempted to include five BNPL firms (PayPal, Block/Afterpay, Affirm, Klarna, and Sezzle) to capture approximately 95% of US BNPL market share. However, data availability constraints required us to exclude two firms. Block/Afterpay (SQ) was excluded due to data retrieval issues from Yahoo Finance during the analysis period. Klarna (KLAR) was excluded because it completed its initial public offering in September 2025, after my sample period ends in August 2025, making historical trading data unavailable for the full analysis window. The three firms included (PayPal, Affirm, and Sezzle) represent substantial BNPL market coverage. PayPal's BNPL product (Pay in 4) represents 68.1% of US BNPL market share, making it the largest BNPL provider. Affirm is a pure-play

BNPL provider that went public in 2021 and represents a significant portion of the market. Sezzle is also a pure-play BNPL provider that went public in 2020. Together, these three firms provide comprehensive coverage of the BNPL sector while ensuring data availability throughout the entire sample period.

For the **Average Credit Card Companies Return**, I take the simple average of monthly stock returns across three credit card companies: **Capital One (COF)**, **Synchrony Financial (SYF)**, and **American Express (AXP)**.

Firm Selection Rationale for Credit Card Companies Group: I selected these three firms because they are US publicly traded credit card companies that represent different segments of the credit card market, providing comprehensive coverage of established credit card providers. Capital One (COF) is a major bank holding company that issues credit cards and operates as one of the largest credit card issuers in the United States. Synchrony Financial (SYF) is a consumer financial services company that specializes in private-label credit cards and co-branded credit cards, partnering with retailers and other businesses. American Express (AXP) is a diversified financial services company that issues charge cards and credit cards, operating both as a card issuer and a payment network. All three firms are publicly traded, have sufficient trading history covering my sample period (February 2020 to August 2025), and represent different business models within the credit card industry (general-purpose cards, private-label cards, and charge cards). Both groups consist of US publicly traded companies that provide consumer credit, making them comparable for volatility analysis.

Each point on the chart represents one month's sector average return. I calculate monthly returns for each stock as (Price_end_of_month - Price_start_of_month) / Price_start_of_month × 100%, then average within each group. I repeat this process for every month, creating two time series: one for BNPL returns and one for credit card company returns. The chart connects these monthly averages with lines, allowing visual comparison of volatility patterns between the two sectors.

Empirical Results: The analysis reveals that BNPL exhibits significantly higher volatility than credit card companies, with a monthly volatility (standard deviation) of **20.46%** compared to credit card companies' volatility of **9.93%**. This results in a volatility ratio of **2.06x**, indicating that BNPL is more than twice as volatile as established credit card companies. The Pearson correlation coefficient between BNPL and credit card company returns is **0.537**, indicating a moderate positive correlation. This suggests that while both sectors share some common drivers (likely broader financial market conditions and consumer credit trends), BNPL exhibits substantially higher volatility, reflecting investor perceptions of greater risk. The 2.06x volatility ratio suggests that BNPL faces unique risks, such as interest rate sensitivity, business model fragility, and regulatory uncertainty, that may limit its ability to sustainably compete with traditional credit cards. This higher volatility could affect BNPL's cost of capital and long-term viability, potentially constraining its growth potential relative to established credit providers.

If BNPL is significantly more volatile than credit card companies, it suggests BNPL faces unique risks (e.g., interest rate sensitivity, business model fragility, regulatory uncertainty) that may limit its ability to sustainably compete with credit cards. Higher volatility could indicate investors perceive BNPL as riskier, which could affect BNPL's cost of capital and long-term viability. Conversely, if BNPL volatility is similar to credit cards, it suggests BNPL may be a viable alternative to credit cards, supporting the view that BNPL could be a meaningful threat to traditional credit card companies.

Understanding BNPL's volatility relative to credit cards helps assess how investors perceive BNPL's risk relative to established credit providers, whether BNPL's business model can sustain long-term competition with credit cards, and what policy implications arise from BNPL's risk profile. This analysis provides important context for evaluating BNPL's role in the consumer credit market and its potential impact on traditional financial institutions.

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