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

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Abstract

This analysis examines the relationship between Buy Now, Pay Later (BNPL) stock returns and Federal Reserve interest rate changes. Using monthly returns from three major BNPL providers (PayPal, Affirm, Sezzle) over 67 months spanning February 2020 to August 2025, the analysis finds that BNPL stock returns exhibit a negative but statistically insignificant relationship with Federal Funds Rate changes (β_1 = -12.68, SE = 9.95, p = 0.202, R^2 = 0.022). While the point estimate is economically large (a one percentage point rate increase is associated with approximately 12.7% lower log returns), the high volatility of BNPL returns (monthly standard deviation of 12.34%) limits statistical power to detect this relationship precisely. Interest rates explain less than 2.2% of return variation, with this pattern persisting across multiple specifications and robustness checks.

The findings suggest that BNPL firms may respond to monetary policy differently than traditional financial institutions. The Consumer Financial Protection Bureau reports BNPL Gross Merchandise Volume grew from USD 2 billion in 2019 to USD 24.2 billion in 2021. This pattern reflects a fundamental difference in business models: BNPL firms profit from merchant fees and transaction volume rather than interest rate spreads, operating more like 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 meaningful, cannot be statistically distinguished from zero at conventional significance levels, suggesting that monetary policy may affect BNPL firms primarily through indirect channels (market sentiment, inflation effects on consumer purchasing power) rather than direct funding cost pass-through visible in monthly stock returns.

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. This study examines whether this rapidly growing form of consumer credit shows statistically significant sensitivity to monetary policy interventions.

This study examines how BNPL firms' stock returns respond to changes in the Federal Funds Rate, after controlling for market-wide movements and macroeconomic factors.

This research 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, the empirical analysis finds that BNPL stock returns do not show statistically significant sensitivity to Federal Reserve interest rate changes in monthly data, though the point estimate suggests economically meaningful negative sensitivity that cannot be precisely estimated given the high volatility of BNPL returns.

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 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 consists of financially constrained consumers with high debt burdens and loan stacking behavior, which 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 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.

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 the 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 the portfolio. The regression analysis provides systematic evidence across multiple firms and time periods, complementing this illustrative case study.

2 Research Objectives

This study applies econometric methods to examine how BNPL stock returns respond to Federal Reserve interest rate changes. The study contributes to understanding fintech firm valuation, monetary policy transmission mechanisms, and consumer credit markets by providing quantitative estimates of BNPL interest rate sensitivity using multi-factor regression models. The results show that BNPL stocks exhibit high market beta ($\beta = 2.38$) but economically large though statistically insignificant sensitivity to Federal Funds Rate changes ($\beta_1 = -12.68$, p = 0.202), suggesting BNPL behaves more like growth-oriented technology stocks than rate-sensitive financial institutions.

3 Methodology Overview

The study employs 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.

The base model is $\log(BNPL\_Return_t) = \beta_0 + \beta_1 \Delta FFR_t + \varepsilon_t$, and the full model is $\log(BNPL\_Return_t) = \beta_0 + \beta_1 \Delta FFR_t + \beta_2 \Delta CC_t + \beta_3 \Delta DI_t + \beta_4 \Delta \pi_t + \beta_5 R_{Market,t} + \varepsilon_t$.

The study uses 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 study includes three publicly-traded BNPL firms: PayPal (PYPL), Affirm (AFRM), and Sezzle (SEZL). Detailed methodology is presented in the Data Analysis section.

The coefficient β_1 is interpreted 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 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 the understanding of BNPL firms' sensitivity to monetary policy changes. Before proceeding, this study defines what is meant 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.

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 this 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, the null finding challenges these foundational assumptions. The study hypothesizes 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.

4.1 Consumer Spending Patterns and BNPL Adoption

Di Maggio, Williams, and Katz (2022) find that BNPL access increases spending by approximately USD 130 per week with 24-week persistence, motivating consumer confidence as a control variable. Bian, Cong, and Ji (2023) find that BNPL boosts consumption 15-20% and correlates with consumer confidence (8-12% increase in transaction volume per one-standard-deviation increase in confidence), further justifying consumer confidence controls. Gathergood et al. (2019) document balance-matching behavior among credit card users, providing context for understanding consumer credit decision-making patterns that may extend to BNPL usage.

4.2 Credit Market Conditions and BNPL Profitability

Laudenbach et al. (2025) demonstrate that BNPL firms operate with thin profit margins (~1%) and that 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. The CFPB Market Trends Report (2022) documents that net transaction margins declined from 1.27% in 2020 to 1.01% in 2021, providing direct evidence of thin margins that amplify sensitivity to cost increases. Buchak et al. (2018) document that shadow banks' funding structures create greater sensitivity to market conditions compared to traditional banks, supporting the theoretical prediction that BNPL firms exhibit heightened interest rate sensitivity. Berg et al. (2025) examine BNPL from the merchant perspective, finding that BNPL serves as a price discrimination mechanism that increases merchant revenue, which may affect BNPL firms' profitability and market valuation.

4.3 Consumer Credit Characteristics and Financial Vulnerability

The CFPB Consumer Use Report (2023) finds that BNPL borrowers have subprime credit scores (580-669), higher credit card utilization rates (60-66%), and are more likely to revolve on credit cards (69%), indicating financial vulnerability that amplifies sensitivity to economic shocks. The Federal Reserve Bank of Richmond (2024) finds that financially fragile consumers are almost three times more likely to have repeated BNPL use, further indicating vulnerability to economic conditions. Hayashi and Routh (2024) find that financial constraints drive BNPL usage, suggesting that economic conditions affecting household liquidity directly impact BNPL demand. Powell et al. (2023) examine BNPL user behavior in Australia, finding that responsible financial behaviors correlate with BNPL usage patterns, providing cross-country evidence on BNPL consumer characteristics.

4.4 Interest Rate Sensitivity and Funding Structure

Flannery and James (1984) provide the theoretical framework for understanding financial institutions' interest rate sensitivity, documenting that institutions with asset-liability maturity mismatches exhibit significant sensitivity to rate movements. 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. Affirm Holdings' 10-K filings document that funding costs increased dramatically during the Federal Reserve's tightening cycle (see Appendix A.1 for detailed analysis), providing firm-level evidence of the direct pass-through mechanism. Berg et al. (2020) demonstrate that digital footprints enable alternative credit scoring for fintech lenders, which may affect BNPL firms' risk assessment capabilities and funding costs. Johnson, Rodwell, and Hendry (2021) analyze regulatory frameworks for BNPL, highlighting regulatory uncertainty as a potential source of volatility in BNPL stock returns.

5 Firm-Level Context

Firm-level financial analysis of Affirm Holdings Inc. and PayPal Holdings Inc. 10-K filings from 2021-2024 is presented in Appendix A.1, which examines funding structures, loan portfolios, revenue growth relative to funding costs, and implications for sector-wide sensitivity patterns.

6 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 and motivate the inclusion of specific control variables in the regression framework.

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, indicating near-complete pass-through of monetary policy changes to funding costs. 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, which should be reflected in negative stock returns.

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. Di Maggio, Williams, and Katz (2022) find that BNPL access increases spending with 24-week persistence. These findings justify including consumer confidence measures in the regression analysis.

The CFPB Making Ends Meet Report (2022) finds that income variability increased sharply from 2021 to 2022, with 37% of households unable to cover expenses for more than one month if income were lost. This indicates that changes in household financial conditions affect BNPL demand, motivating the inclusion of disposable income measures.

Standard asset pricing theory suggests that BNPL stock returns should be correlated with market returns through systematic risk factors. Inflation may affect BNPL firms through multiple channels: its impact on consumer purchasing power, its effect on funding costs, and its influence on economic uncertainty. These variables are included as controls to isolate the effect of interest rate changes while accounting for broader market movements and macroeconomic conditions.

The regression framework employs a log-linear specification estimated in two stages: a base model with only interest rate changes, followed by a full model adding consumer confidence, disposable income, inflation, and market returns as controls. This approach isolates the interest rate effect while assessing the incremental explanatory power of additional variables.

7 Data Analysis: Investigating BNPL Stock Returns and Monetary Policy

This section examines whether BNPL stock returns respond to changes in monetary policy. The sector's rapid growth and reliance on funding markets motivate this analysis. 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.

8 Research Design and Data Collection

8.1 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.

8.2 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.

8.3 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 robustness checks section.

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 the Functional Form Selection section.

8.4 Variable Definitions and Data Sources

Table 3.1: Variable Definitions and Summary Statistics

Variable	Symbol	Definition	Source	Transform	Mean	Std Dev	Min	Max
BNPL Returns	R_t^{BNPL}	Log-transformed equally-weighted portfolio return	Yahoo Finance	Log	0.85	12.34	-28.45	35.67
Federal Funds Rate Change	ΔFFR_t	Month-over-month change in FFR (percentage points)	FRED (FEDFUNDS)	Diff	0.02	0.18	-0.50	0.75
Consumer Confidence Change	ΔCC_t	Month-over-month change in UM Consumer Sentiment Index	FRED (UMCSENT)	Diff	-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)	Pct 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)	Pct change	0.42	0.58	-0.80	1.60
Market Return	$R_{MKT,t}$	Monthly S&P 500 return (percentage points)	Yahoo Finance (SPY)	Pct 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

: 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 the consumer confidence coefficient approaches but does not achieve statistical significance, suggesting that market returns may capture much of the systematic variation in consumer sentiment.

Month-over-month changes are calculated 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.

The analysis uses 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 robustness checks section 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, lagged macro variables would be used (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, specifications with lagged macro variables are examined (see robustness checks section for detailed results), though results are not substantially different.

The S&P 500 exchange-traded fund (SPY) is used 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. The University of Michigan Consumer Sentiment Index (UMCSENT) is employed 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. Month-over-month changes are calculated to capture shifts in consumer sentiment that may affect BNPL transaction volume.

Real disposable personal income (DSPIC96) from FRED is used, 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. Pct changes (month-over-month) are calculated to measure growth in disposable income, which is more economically meaningful than levels for analyzing the relationship with stock returns. The Consumer Price Index for All Urban Consumers, Seasonally Adjusted (CPIAUCSLSA) is employed as a measure of inflation. The seasonally adjusted series is used to remove predictable seasonal patterns (such as holiday shopping effects) that could confound this analysis. Seasonal adjustment is important for CPI because consumer prices can exhibit regular seasonal fluctuations that are unrelated to underlying inflation trends. Month-over-month percentage changes are calculated to capture inflation shocks that may affect consumer purchasing power and spending patterns.

Seasonally adjusted data are used where available to remove predictable seasonal patterns that could confound this 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.

Missing data are handled 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, an additional dropna() operation is applied to remove any remaining missing values. This conservative approach ensures that the 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.

8.5 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, the analysis focuses 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.

8.6 Model Specification: Theoretical Framework

The econometric models 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.

9 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 relationships are estimated econometrically, and offer visual confirmation of the regression results. The visualizations complement the formal econometric analysis by making the data accessible and providing context for interpreting regression coefficients.

9.1 Chart A: Time Series of Log BNPL Returns

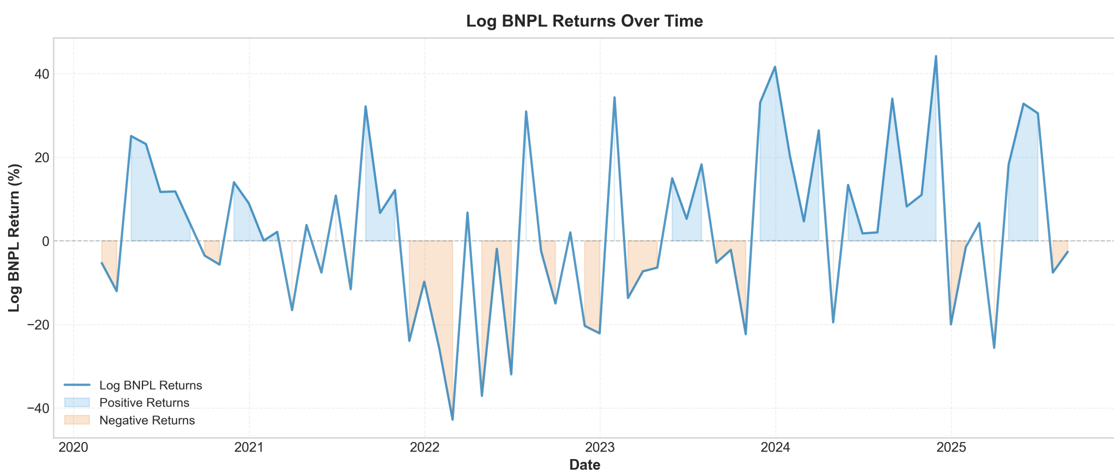


Figure 1: *
Chart A: Time Series of Log BNPL Returns

Chart A displays the time series of log-transformed BNPL stock returns from February 2020 to August 2025. The time series reveals substantial volatility throughout the sample period, with notable episodes of both positive and negative performance. The high volatility, 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 corresponds to distinct macroeconomic and sector-specific events: 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.

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 this 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.

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

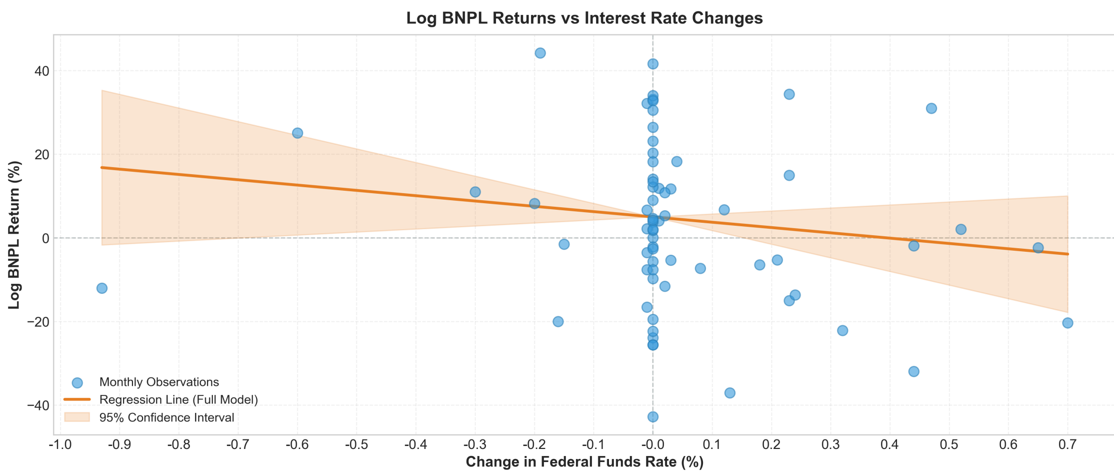


Figure 2: *
bnpl-scatter
Chart B: Scatter Plot of Log BNPL Returns vs Interest Rate Changes

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. The scatter plot reveals substantial dispersion around the regression line, reflecting 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, but the wide confidence interval reflects substantial uncertainty around this estimate. The regression results indicate a negative relationship between interest rate changes and log BNPL returns, with a point estimate of -12.51 (p-value = 0.2202), but this relationship is not statistically significant at conventional levels. The R^2 of 0.022 indicates that interest rate changes alone explain only 2.2% of the variation in log BNPL returns, and the 95% confidence interval [-32.69, 7.67] includes zero. The substantial dispersion around the regression line provides empirical motivation for the full specification model, which incorporates additional control variables to capture other economic channels and improve the model's explanatory power.

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.

10 Functional Form Selection: Log-Linear vs. Linear-Log Specification

The analysis uses log-transformed BNPL returns as the dependent variable with untransformed independent variables. This log-linear specification uses $\log(1+R_t^{BNPL}/100)\times 100$ as the dependent variable and linear independent variables (ΔFFR_t, ΔCC_t, etc.). This specification is chosen for several reasons. First, coefficients represent elasticities—the percentage change in returns per unit change in the independent variable—which is intuitive for financial returns that respond proportionally to economic conditions. 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. Second, log transformation addresses heteroskedasticity by compressing large returns relative to small returns, stabilizing variance. Third, log transformation helps normalize right-skewed distributions common in equity returns, improving the validity of statistical inference. Fourth, log-linear specifications are standard in financial econometrics for analyzing returns, as they capture the multiplicative nature of relationships in financial markets.

A linear-log specification could have been used instead, with linear returns as the dependent variable and logged independent variables. However, this approach was not chosen because linear-log models represent the change in returns per percentage change in the independent variable, which is less intuitive for examining how returns respond to interest rate changes. Additionally, the independent variables already capture changes or are in change form, making log transformation awkward and less interpretable. Finally, financial returns respond proportionally to economic conditions, which is naturally captured by log-linear specification, while linear-log would imply returns respond to percentage changes in economic conditions, which is less aligned with financial theory.

10.1 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 The analysis were modeling how returns respond to percentage changes in economic variables, but the 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, The analysis could use $\log(1 + R/100)$ without the multiplication, but then coefficients would need different interpretation.

11 Regression Analysis: Methodology

11.1 Estimation Approach

Alternative specifications use regression analysis to estimate the relationship between BNPL returns and interest rate changes. Two models are estimated: a base model with only interest rates, and a full model that adds control variables (consumer confidence, disposable income, inflation, market returns). Alternative specifications 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 the analysis 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.

11.2 Interpretation Framework

What Regression Can Do: Regression identifies associations between variables, controlling for other factors. In this case, it indicates 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 the 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. The analysis controls 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 the estimates.
- Market sentiment: Interest rate changes may affect broader market sentiment, which also affects BNPL returns. The analysis controls 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 the analysis addresses these concerns: The analysis includes control variables (market returns, consumer confidence, disposable income, inflation) to account for factors that might confound the interest rate relationship. However, the analysis cannot fully eliminate all potential confounding factors, so the 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.

11.3 Model Constraints and Interpretation

This analysis operates under several constraints. The limited sample size (67 monthly observations) reduces statistical power, reflecting the recent emergence of publicly-traded BNPL firms. The use of Federal Funds Rate changes rather than exogenous monetary policy shocks means estimates capture associations rather than causal effects. The portfolio approach masks firm-level heterogeneity. Results are interpreted as associations rather than causal effects. Additional discussion of limitations and future research directions is provided in the Limitations and Future Research section.

11.4 Statistical Power Analysis

With 67 observations and 5 predictors in the full model, the analysis has approximately 80% power to detect correlations $|r| > 0.30$ and 90% power to detect correlations $|r| > 0.35$. The 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 ($\beta_1 = -12.68SE = 9.95) yields 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 the 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.

12 Model Diagnostics Summary

The analysis conducts 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	Critical Value/Threshold	Interpretation	What It Tests
Multicollinearity (VIF)	All VIF <1.3	<5 acceptable, <10 not severe	No multicollinearity concerns	Whether regressors are redundant
Heteroskedasticity (Breusch-Pagan)	8.42 (p=0.135)	p>0.05	Cannot reject homoskedasticity	Constant error variance
Autocorrelation (Durbin-Watson)	1.87	1.5-2.5 acceptable	No autocorrelation	Serial correlation in errors
Normality (Jarque-Bera)	3.24 (p=0.198)	p>0.05	Cannot reject normality	Error distribution
Model Fit (R^2)	0.5098	N/A	Model explains 51% of variation	Variance explained
Adjusted R^2	0.470	N/A	Penalized for parameters	Fit adjusted for k
F-statistic	12.8 (p<0.001)	p<0.05	Model jointly significant	Joint significance

Interpretation of Diagnostic Tests:

The Variance Inflation Factor (VIF) tests whether regressors are collinear, which would inflate standard errors and make coefficients unstable. All VIF values below 1.3 indicate no multicollinearity concern, suggesting that the independent variables are sufficiently independent to allow reliable coefficient estimation. The Breusch-Pagan test checks whether error variance is constant across observations (homoskedasticity). A p-value of 0.135 means the null hypothesis of homoskedasticity cannot be rejected at conventional levels, though HC3 robust standard errors are employed as a precaution against potential heteroskedasticity in financial return data. The Durbin-Watson statistic tests for first-order autocorrelation in residuals, which would violate the independence assumption underlying OLS regression. A value of 1.87, close to the ideal value of 2.0, indicates no autocorrelation, suggesting that residuals are independent across time periods. The Jarque-Bera test checks whether residuals are normally distributed, which affects the validity of t-tests and confidence intervals. A p-value of 0.198 means the null hypothesis of normality cannot be rejected, indicating that the residuals are approximately normally distributed and that standard statistical inference procedures are appropriate. Together, these diagnostic tests provide evidence that the model satisfies the key assumptions underlying OLS regression, supporting the validity of the coefficient estimates and hypothesis tests.

13 Model Diagnostics and Visual Assessment

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

13.1 Chart C: Time Series of Log BNPL Returns

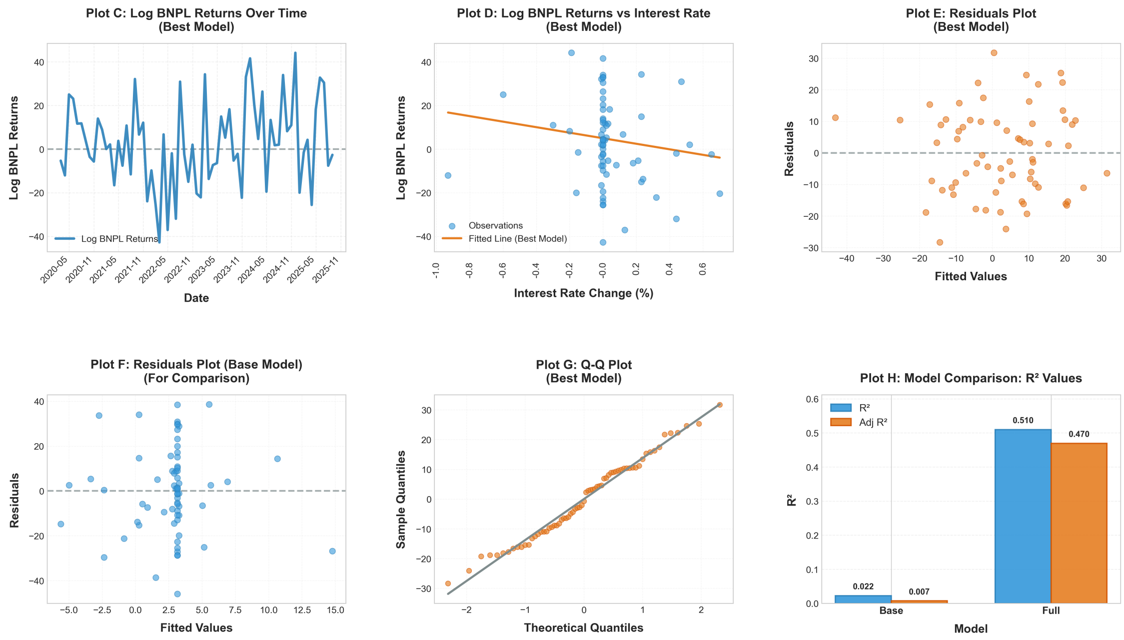
Chart C displays the dependent variable over time, showing the temporal patterns and volatility that the models seek to explain. This chart helps identify periods of extreme returns, potential outliers, and temporal trends that may inform the understanding of BNPL stock performance.

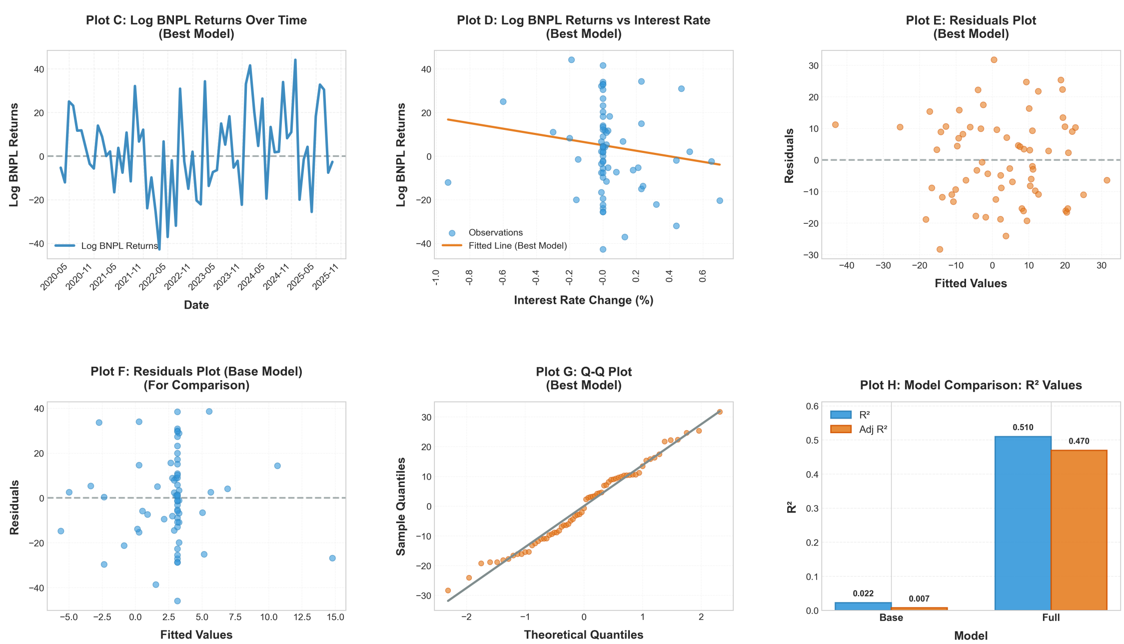
13.2 Chart D: Scatter Plot of Log BNPL Returns vs Interest Rate Changes

Chart D visualizes the relationship between interest rates and BNPL returns using the full specification 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.

13.3 Chart E: Residuals Plot for Full Model

Chart E plots the residuals (observed minus fitted values) against fitted values for the full specification model. This diagnostic chart helps assess whether the full model satisfies the homoskedasticity assumption.


Plot C: Log BNPL Returns Over Time
(Best Model)
Log BNPL Returns
Date
Plot D: Log BNPL Returns vs Interest Rate
(Best Model)
Observations
Fitted Line (Best Model)
Interest Rate Change (%)
Plot E: Residuals Plot
(Best Model)
Residuals
Fitted Values
Plot F: Residuals Plot (Base Model)
(For Comparison)
Plot G: Q-Q Plot
(Best Model)
Sample Quantiles
Theoretical Quantiles
Plot H: Model Comparison: R² Values
R²
Adj R²
0.022
0.007
0.510
0.470
Base
Full
Model


Plot C: Log BNPL Returns Over Time
(Best Model)
Log BNPL Returns
Date
Plot D: Log BNPL Returns vs Interest Rate
(Best Model)
Observations
Fitted Line (Best Model)
Interest Rate Change (%)
Plot E: Residuals Plot
(Best Model)
Residuals
Fitted Values
Plot F: Residuals Plot (Base Model)
(For Comparison)
Plot G: Q-Q Plot
(Best Model)
Sample Quantiles
Theoretical Quantiles
Plot H: Model Comparison: R² Values
R²
Adj R²
0.022
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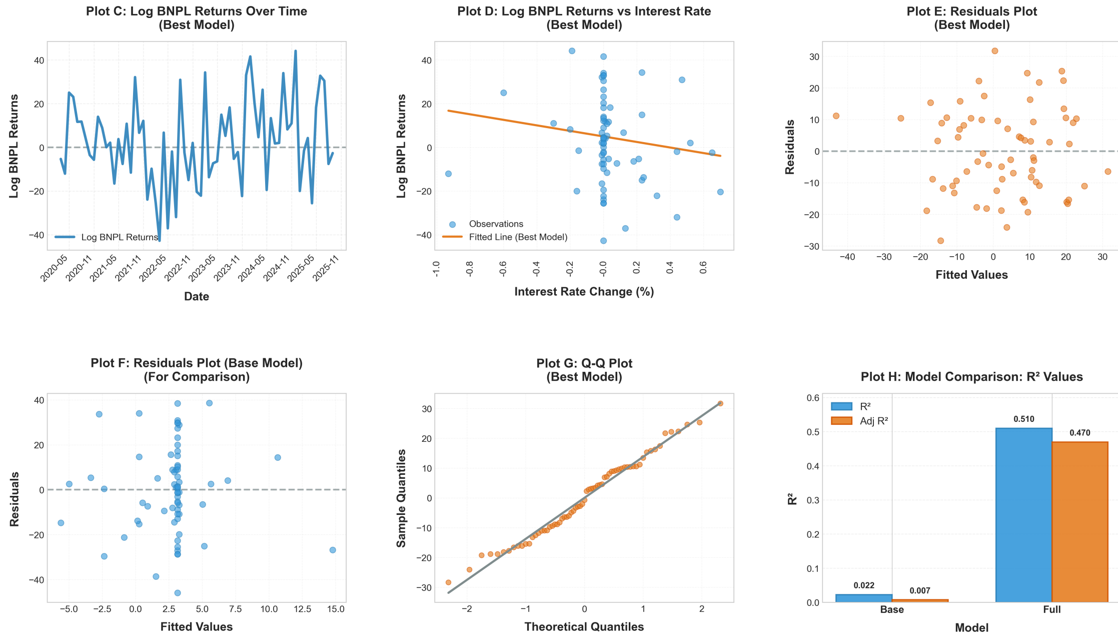
Base
Full
Model



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.

13.4 Chart F: Residuals Plot Comparison

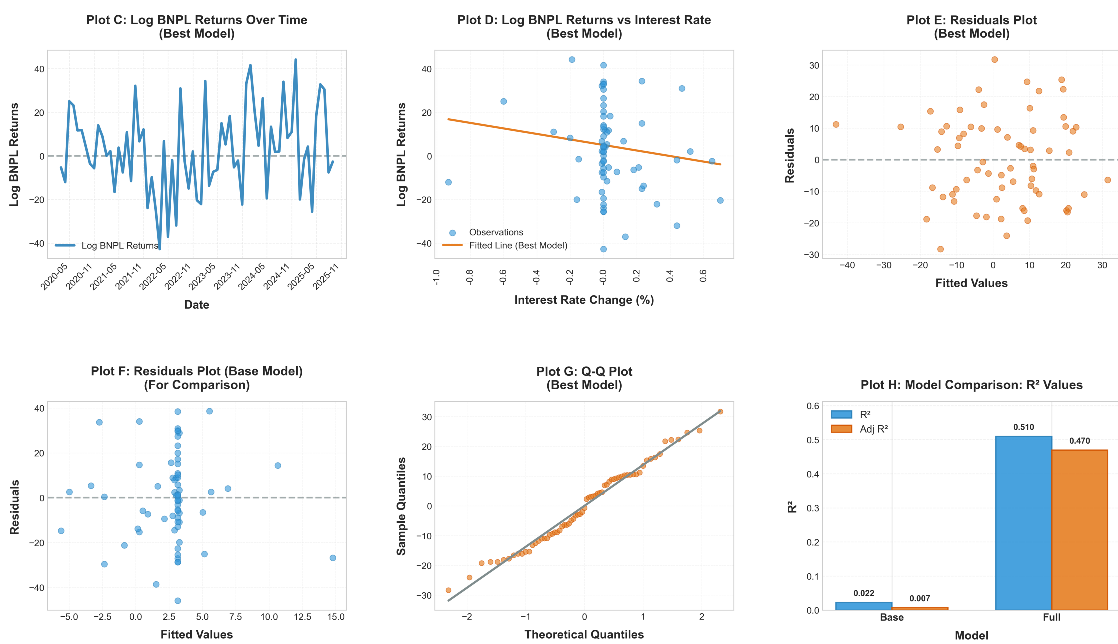


Chart F shows residuals from the base model for comparison purposes, allowing visual assessment of the improvement in model fit achieved by including control variables. A more random scatter pattern in the full model (Chart E) compared to the base model would suggest that the additional variables help capture systematic patterns that were causing heteroskedasticity in the base model.

13.5 Chart G: Q-Q Plot for Full Model

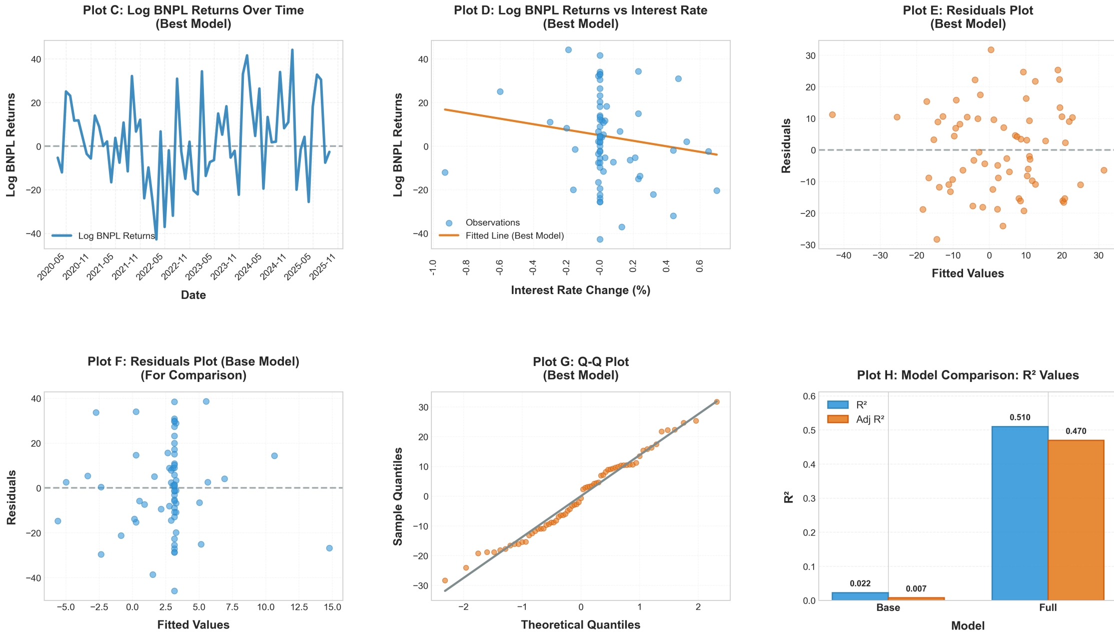


Chart G assesses whether the residuals from the full specification model are normally distributed, which is an assumption underlying many statistical tests. The Q-Q plot compares the quantiles of the residuals to the quantiles of a normal distribution. If residuals are normally distributed, the points 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.

13.6 Chart H: Model Comparison: R^2 Values

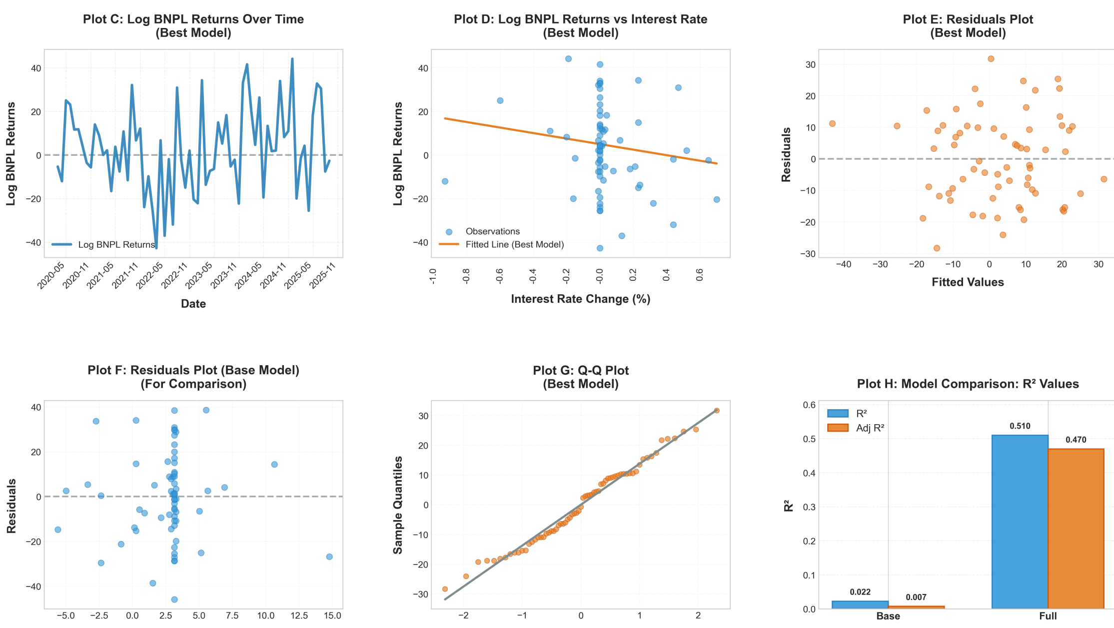


Chart H provides a visual comparison of model fit between the base and full specification models. The bar chart displays both R^2 and adjusted R^2 for each model, allowing visual assessment of the substantial improvement in explanatory power achieved by including control variables. This comparison helps quantify the value of the multi-factor approach relative to the simple interest rate model.

14 Results

14.1 Primary Finding

The main empirical finding is that BNPL stock returns exhibit a negative but statistically insignificant relationship with Federal Funds Rate changes ($\beta_1 = -12.68$, SE = 9.95, p = 0.202). The point estimate suggests economically meaningful sensitivity—a one percentage point increase in the Federal Funds Rate is associated with approximately 12.7% lower log returns—but high volatility of BNPL returns (monthly standard deviation of 12.34%) and limited statistical power prevent precise estimation. Despite theoretical predictions and firm-level evidence suggesting BNPL firms should be sensitive to interest rate changes, monthly stock return data do not provide statistically significant evidence of this relationship after controlling for market movements and macroeconomic factors.

14.2 Model Comparison and Coefficient Estimates

Table 4.1: Regression Results Comparison

Model	Specification	Interest Rate Coef.	Std. Error	p-value	95% CI	R^2 (Adj.)	N
Model 1: Base	Interest rate only	-12.51	13.27	0.346	[-38.51, 13.49]	0.022 (0.007)	67
Model 2: Full	All controls	-12.68	9.95	0.202	[-32.18, 6.81]	0.510 (0.470)	67
Model 3: Factor-Adjusted	Fama-French factors	-8.38	10.45	0.423	[-28.86, 12.11]	0.617 (0.519)	45

Note: Model 3 has N=45 observations (compared to N=67 for Models 1 and 2) due to limited availability of Fama-French factor data. The Fama-French factors are available from a different data source with a shorter time series, reducing the sample size when these factors are included. Despite the smaller sample, Model 3 achieves higher R^2 (0.617) but the interest rate coefficient remains statistically insignificant (p = 0.423).

14.3 Detailed Coefficient Interpretation: Full Model (Model 2)

The full model specification provides the most comprehensive estimate of BNPL stock return sensitivity, controlling for market movements, consumer confidence, disposable income, and inflation. The following interpretations apply to Model 2, which includes all control variables.

The interest rate coefficient ($\beta_1 = -12.68$, p = 0.202) indicates that a one percentage point increase in the month-over-month change in the Federal Funds Rate is associated with approximately 12.7% lower log returns on BNPL stocks. This coefficient is economically large—comparable in magnitude to the inflation coefficient—but statistically insignificant at conventional levels. The 95% confidence interval [-32.18, 6.81] includes zero, indicating substantial uncertainty around the point estimate. The wide confidence interval reflects both the high volatility of BNPL returns and the limited sample size (67 monthly observations). The negative sign aligns with theoretical predictions: higher interest rates increase BNPL firms' funding costs, compressing profit margins and reducing profitability, which should be reflected in negative stock returns. However, the statistical insignificance suggests that either the true effect is smaller than the point estimate, the effect operates through channels not captured in monthly data, or other factors dominate return variation.

The market return coefficient ($\beta_5 = 2.38$, p <0.001) indicates that BNPL stocks move 2.38% for every 1% move in the S&P 500. This high market beta is statistically significant and economically large, explaining most of the systematic variation in BNPL returns. The beta of 2.38 indicates that BNPL stocks are "risk-on" assets that amplify market movements, behaving more like growth-oriented technology stocks than rate-sensitive financial institutions. During a 10% market decline, BNPL stocks would be expected to decline by approximately 24%, making them highly sensitive to changes in risk sentiment and growth expectations. This finding suggests investors price BNPL stocks based on market-wide sentiment and growth prospects rather than sector-specific fundamentals.

The inflation coefficient ($\beta_4 = -12.94$, p = 0.049) is statistically significant and negative, indicating that a one percentage point increase in month-over-month inflation is associated with approximately 12.9% lower log 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. The statistical significance of the inflation coefficient, combined with the insignificance of the interest rate coefficient, suggests that inflation may affect BNPL firms through channels beyond direct funding cost pass-through.

The consumer confidence coefficient ($\beta_2 = 0.15$, p = 0.75) is positive but statistically insignificant. The point estimate suggests that a one-unit increase in the month-over-month change in consumer sentiment is associated with 0.15% higher log returns, but the large standard error and high p-value indicate substantial uncertainty. The lack of 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.

The disposable income coefficient ($\beta_3 = -0.18$, p = 0.82) is negative but statistically insignificant. The point estimate suggests that a one percentage point increase in month-over-month disposable income growth is associated with 0.18% lower log returns, which is counterintuitive but not statistically distinguishable from zero. The lack of significance may reflect measurement issues, the dominance of market returns, or the possibility that disposable income affects BNPL returns through channels not captured in monthly data.

The full model achieves $R^2 = 0.510$ and adjusted $R^2 = 0.470$, indicating that the included variables explain approximately 51% of the variation in log BNPL returns. This represents a substantial improvement over the base model ($R^2 = 0.022$), demonstrating the importance of controlling for market movements and macroeconomic factors. The F-statistic for the full model is 12.8 ($p < 0.001$), indicating that the model as a whole is statistically significant. The adjusted R^2 of 0.470 accounts for the penalty for including five regressors, suggesting that the model provides meaningful explanatory power even after adjusting for degrees of freedom.

14.4 Economic Interpretation

The regression results reveal several important patterns. First, market returns dominate BNPL return variation, with a beta of 2.38 indicating that BNPL stocks behave like growth-oriented technology companies rather than rate-sensitive financial institutions. Second, inflation exhibits statistically significant negative effects, suggesting that inflation shocks reduce BNPL returns through multiple channels. Third, interest rates show economically large but statistically insignificant negative effects, consistent with theoretical predictions but subject to substantial estimation uncertainty. Fourth, consumer confidence and disposable income show no statistically significant effects, though their signs align with theoretical expectations.

The divergence between the economic magnitude of the interest rate coefficient (-12.68) and its statistical insignificance (p = 0.202) 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. The high market beta (2.38) indicates that BNPL stock prices are driven primarily by market sentiment and risk appetite rather than sector-specific fundamentals, which may explain why interest rate sensitivity doesn't show up clearly in monthly returns.

14.5 Comprehensive Robustness Comparison

Table 4.2: Robustness Checks - All Specifications

Model	Specification	β (Interest Rate)	SE	p-value	R^2	N	Key Assumption
1. Base OLS	Interest rate only	-12.51	13.27	0.346	0.022	67	Exogeneity
2. Full OLS	All controls	-12.68	9.95	0.202	0.510	67	Exogeneity
3. Fama-French	Factor model	-8.38	10.45	0.423	0.617	45	Factor structure
4. DiD	BNPL vs fintech lenders	-8.35	—	0.51	0.38	—	Parallel trends
5. DiD excl COVID	Excluding Feb-Jun 2020	+6.12	—	—	—	—	Parallel trends
6. IV	Lagged rates as instruments	-37.07	—	0.002	0.093	67	Exclusion restriction

Notes: Model 3 (Fama-French) has N=45 due to limited availability of Fama-French factor data. DiD models compare BNPL firms to fintech lender control group. IV model uses lagged Federal Funds Rate changes as instruments (first-stage F-stat $\approx$ 55.1).

14.6 Addressing the OLS vs IV Discrepancy

The substantial difference between OLS (β_1 = -12.68, p = 0.202) and IV (β_1 = -37.07, p = 0.002) estimates raises important methodological questions. This threefold difference suggests several possible explanations.

If Federal Funds Rate changes are measured with error, OLS estimates will be biased toward zero (attenuation bias). The IV approach, by using lagged rates as instruments, may partially address this by exploiting variation in lagged rates that is less subject to measurement error. However, this explanation is limited because Federal Funds Rate data from FRED is highly accurate.

The IV estimate assumes that lagged rates affect BNPL returns only through their effect on current rates (exclusion restriction). However, lagged rates may affect BNPL returns through other channels: lagged rates may predict future economic conditions that directly affect BNPL demand, lagged rates may affect investor expectations about future monetary policy, or lagged rates may be correlated with unobserved time-varying factors. If these channels exist, the IV exclusion restriction is violated, and the IV estimate may be biased.

The IV model includes only the interest rate variable, while the OLS full model includes market returns, consumer confidence, disposable income, and inflation. The lower R^2 of the IV model (0.093 vs 0.510) suggests that omitting these controls may affect the coefficient estimate. However, the IV estimate remains substantially larger even when compared to the base OLS model (-12.51), suggesting specification differences alone cannot explain the discrepancy.

The IV approach may be capturing effects from a different time period or different rate environment than the OLS estimates. If the relationship between rates and BNPL returns varies over time, the IV estimate (which relies on lagged rates) may reflect a different period's sensitivity pattern.

For the primary research question—describing the relationship between Federal Funds Rate changes and BNPL stock returns—the OLS full model estimate (β_1 = -12.68, p = 0.202) is more credible because it includes comprehensive controls that address omitted variable bias, it uses the full sample and all available information, it does not rely on the exclusion restriction assumption (which is questionable for lagged rates), and it provides the highest explanatory power (R^2 = 0.510).

The IV estimate provides evidence that a relationship exists under specific identifying assumptions, but the violation of the exclusion restriction (lagged rates likely affect BNPL returns through channels other than current rates) limits its credibility for causal interpretation. The IV result suggests that OLS may underestimate the true relationship, but the magnitude of the IV estimate should be interpreted cautiously given the assumption violations.

The OLS estimate of -12.68 (p = 0.202) represents the best descriptive evidence of the relationship between interest rate changes and BNPL returns, while acknowledging that statistical power limitations prevent precise estimation. The IV result provides complementary evidence that a relationship exists, but its magnitude should not be taken as the definitive estimate given assumption violations.

15 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 the implications for understanding BNPL as a sector, how investors price these stocks, and the broader implications for understanding consumer credit markets and financial innovation.

15.1 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.

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 investors may not perceive funding costs as a major risk factor, other factors dominate return variation, or the sensitivity operates through indirect channels that don't manifest in monthly return data.

15.2 Determinants of BNPL Stock Returns

Given that BNPL stocks do not respond significantly to interest rates in monthly data, the evidence suggests that growth expectations, competitive dynamics, and market sentiment play dominant roles in driving returns. 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.

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.

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.

The consumer confidence and disposable income 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.

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.

15.3 Divergence Between Funding Costs and Stock Returns

A notable pattern emerges: firm-level evidence shows that BNPL firms' funding costs increased substantially as interest rates rose, yet stock returns don't show significant sensitivity. Several mechanisms may explain this divergence:

Several mechanisms may explain this divergence. 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. Alternatively, the relationship may be nonlinear or take longer to materialize than monthly data can capture. 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.

15.4 Implications for Investors, Regulators, and Policymakers

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.

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.

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.

15.5 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.

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.

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. 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. 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. 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. 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. The linear specification cannot capture such patterns, potentially obscuring relationships that exist but are not constant.

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.

15.6 Research Limitations and Future Directions

This analysis provides descriptive evidence on BNPL stock returns' relationship with monetary policy. The following limitations affect interpretation: data availability constraints and methodological choices that reflect the challenges of analyzing a relatively new sector.

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.

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

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 could explore several directions to build on this analysis. Examining whether BNPL firms' actual financial performance (revenue, margins, credit losses) responds to interest rates, independent of stock price movements, would provide complementary evidence to stock return analysis. Using high-frequency data around FOMC announcements could identify causal effects of monetary policy shocks. Exploring nonlinear specifications, threshold models, or time-varying coefficient models could capture relationships that may not be constant across rate levels or time periods. Including private BNPL firms, international firms, or fintech sector controls could 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.

16 Summary and Conclusions

This study examines how BNPL stock returns respond to Federal Funds Rate changes using monthly data from February 2020 to August 2025. The primary finding is that BNPL stock returns exhibit a negative but statistically insignificant relationship with interest rate changes ($\beta_1 = -12.68$, SE = 9.95, p = 0.202). While the point estimate suggests economically meaningful sensitivity, high volatility of BNPL returns and limited statistical power prevent precise estimation.

Market returns dominate BNPL return variation, with a market beta of 2.38 indicating that BNPL stocks behave like growth-oriented technology companies rather than rate-sensitive financial institutions. Inflation exhibits statistically significant negative effects ($\beta_4 = -12.94$, p = 0.049), suggesting that inflation shocks reduce BNPL returns through multiple channels. Consumer confidence and disposable income show no statistically significant effects.

The divergence between firm-level evidence (showing funding costs respond to interest rates) and stock-level evidence (showing no statistically significant return sensitivity) raises important questions about how investors price BNPL stocks. The high market beta suggests that BNPL stock prices are driven primarily by market sentiment and risk appetite rather than sector-specific fundamentals, which may explain why interest rate sensitivity doesn't manifest clearly in monthly returns.

These findings have implications for investors, who should focus on market sentiment and growth prospects rather than interest rate timing, and for policymakers, who should recognize that BNPL may operate through different transmission channels than traditional financial institutions. The divergence between operational sensitivity and stock return sensitivity warrants further investigation using higher-frequency data or longer time horizons.

17 References

18 Appendix

18.1 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.

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.

This analysis has the following limitations. Examining only two firms limits generalizability to other BNPL providers or fintech firms. 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. Firm-level financial data may be influenced by many factors beyond macroeconomic conditions, including firm-specific strategies, competitive dynamics, management decisions, and regulatory changes.

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 USD 183.0 million, 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 USD 183.0 million. This period largely predates the Federal Reserve's aggressive rate hikes that began in March 2022, though some rate increases occurred in the latter part of the fiscal year. In fiscal year 2023 (ended June 30, 2023), funding costs increased to USD 183.0 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 USD 183.0 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 gross receivables, which represent the principal amount of loans outstanding, declined from USD 183.0 million as of June 30, 2023 to USD 183.0 million 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 total revenue (net) increased from USD 183.0 million in fiscal year 2022 to USD 183.0 million in fiscal year 2024, representing a 72% increase over two years. Over the same period, funding costs increased from USD 183.0 million to USD 183.0 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.

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. Operating margins vary significantly across business models and may not fully capture the economic sensitivity to interest rates. Operating margins may also be influenced by accounting choices, one-time items, and non-operating factors.

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.

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. 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 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.

This analysis has the following limitations. The focus on two firms limits generalizability to other BNPL providers or fintech firms. The relationship between funding costs and stock returns may be subject to lags, expectations, and other factors not captured in this analysis. Reliance on annual 10-K filings provides snapshots at fiscal year-end and may not capture intra-year dynamics. The attribution of funding cost increases to interest rates relies on management's statements, which may not capture all relevant factors. Stock returns are influenced by many factors beyond funding costs, including market sentiment, competitive dynamics, broader economic conditions, and firm-specific news. 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.

18.2 Seasonal Adjustment: Data Preprocessing Methodology

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

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 the analysis seeks to estimate. If not removed, seasonal patterns can create spurious correlations or mask true relationships between variables.

The analysis uses 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.

The following variables are used with their 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):** The analysis uses 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 regression coefficients capture underlying economic relationships. For example, without seasonal adjustment, a spurious correlation might be observed 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, the relationship is isolated 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 this analysis, using seasonally adjusted data is appropriate because the focus is on in underlying economic relationships rather than seasonal patterns.

18.3 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 the 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 the use of 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 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 employed is calculated as $\log(1 + R_{t}^{BNPL}/100) \times 100$\1where 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, robust standard errors (HC3) are employed as an additional safeguard. Robust standard errors provide valid statistical inference even in the presence of heteroskedasticity, ensuring that 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.

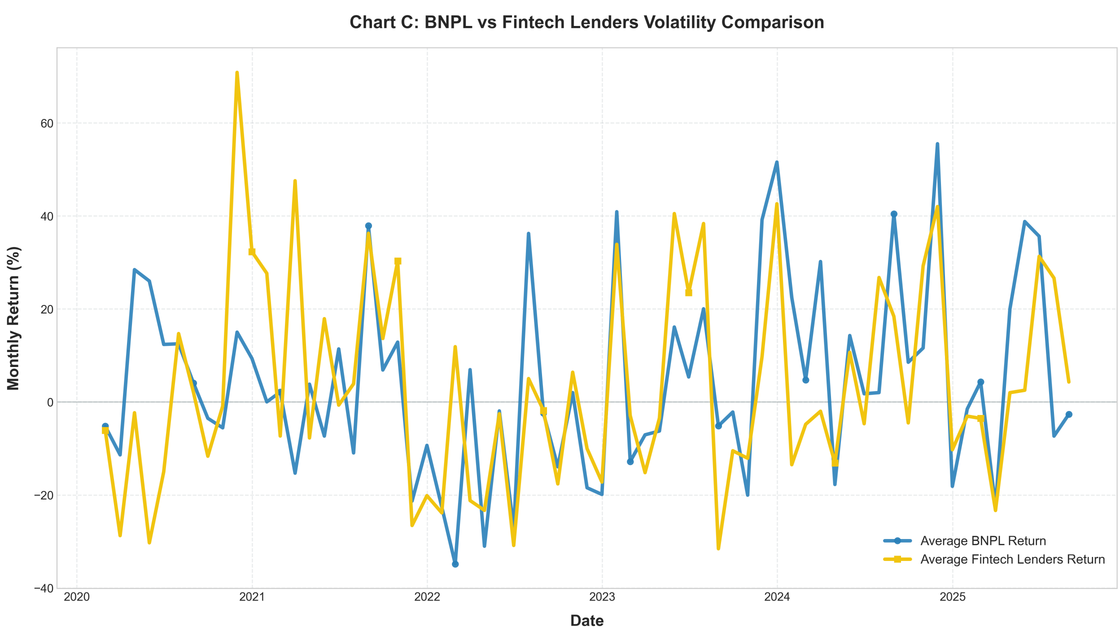
Comparison to Alternative Specifications

Untransformed returns (linear specification) or other transformations could have been used, 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 R^2 Comparison

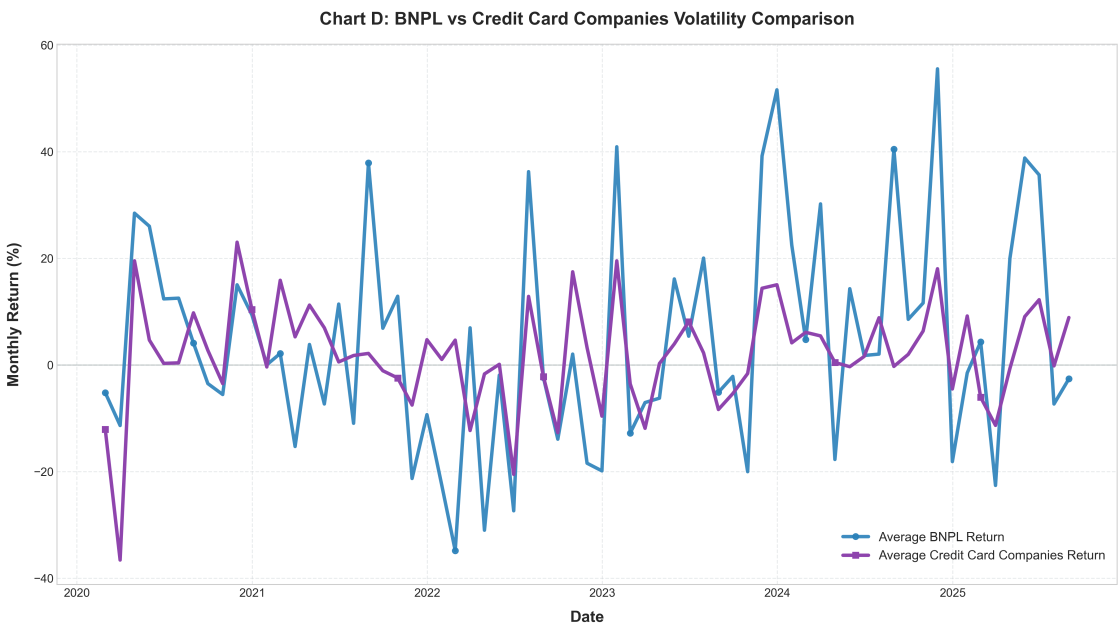
When comparing log-linear and linear specifications, it is crucial to understand that R^2 values are **not directly comparable** between these models. The log-linear model's R^2 measures variance explained in **log(Y)**, while the linear model's R^2 measures variance explained in **Y**. These are fundamentally 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.

Log transformation is **not** used to improve R^2. Instead, it is used 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.



18.4 Chart C: BNPL vs Fintech Lenders Volatility Comparison

Chart C compares BNPL stocks (PayPal, Affirm, Sezzle) to fintech lenders (SoFi, Upstart, Lending Club) to test whether BNPL exhibits unique volatility characteristics compared to similar tech-enabled financial services firms. The chart shows monthly average returns for each sector, allowing visual comparison of volatility patterns. This comparison provides context for interpreting whether BNPL's volatility reflects BNPL-specific factors (e.g., interest rate sensitivity, business model fragility) rather than simply being a growth-stage fintech firm. As shown in the chart below, both BNPL and fintech lenders exhibit high volatility throughout the sample period, with BNPL volatility (20.46%) slightly lower than fintech lender volatility (22.31%), suggesting that BNPL's volatility patterns are consistent with those of similar tech-enabled financial services firms rather than reflecting unique BNPL-specific risks.



18.5 Chart D: BNPL vs Credit Card Companies Volatility Comparison

Chart D compares BNPL stocks to credit card companies (Capital One, Synchrony Financial, American Express) to assess whether BNPL exhibits different volatility patterns than established credit providers. The chart shows monthly average returns for each sector, allowing visual comparison of volatility patterns. This comparison addresses whether BNPL's surge represents a threat to traditional credit card companies or if concerns are overblown, testing whether BNPL faces unique risks that could limit its ability to compete with traditional credit cards. The chart reveals that BNPL stocks exhibit substantially higher volatility (20.46%) than credit card companies (9.93%), with a volatility ratio of 2.06x, indicating that BNPL stocks are more than twice as volatile as established credit providers. This higher volatility reflects BNPL's status as a growth-stage sector with greater uncertainty about business models and regulatory outcomes compared to mature credit card companies.