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

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Tuesday 2nd December, 2025

Abstract

This study examines whether Buy Now, Pay Later (BNPL) stock returns exhibit interest rate sensitivity consistent with firm-level evidence of near-complete funding cost pass-through. Using monthly data from three publicly traded BNPL providers over 66 months (February 2020–August 2025), I employ multi-factor regressions with heteroskedasticity-robust (HC3) standard errors to estimate rate sensitivity while controlling for market movements and macroeconomic conditions. Despite firm-level evidence of near-complete funding cost pass-through (Laudenbach et al., 2025), BNPL stock returns show no statistically significant relationship with interest rates. Instead, BNPL stocks exhibit high market beta (2.38), behaving like growth-oriented technology assets that amplify systematic risk rather than rate-sensitive financial institutions. Market returns explain 52% of BNPL variation versus only 2% for interest rates. A one percentage point increase in the Federal Funds Rate associates with roughly 12–13% lower BNPL returns, an economically meaningful but statistically imprecise estimate. This disconnect suggests investors price BNPL on growth expectations rather than near-term fundamentals, with implications for fintech valuation and monetary policy transmission.

1 Introduction and Research Question

In fiscal year 2024, Affirm Holdings reported funding costs of $650 million, up 88% from the prior year, attributing the increase to higher benchmark rates as the Federal Reserve lifted the policy rate from near zero to above 5%. Over two years, Affirm's funding costs rose 394%, illustrating how monetary tightening transmits directly to BNPL providers via wholesale funding (Laudenbach et al., 2025). Yet over the same period Affirm's stock fell 70% while revenue grew 30%, raising a puzzle: if BNPL firms face clear funding cost sensitivity, do their stock returns reflect this exposure?

This paper investigates whether BNPL stock returns exhibit interest rate sensitivity consistent with firm-level funding pass-through. The question matters because BNPL scaled from $2billioninGMVin2019toaprojected560$ billion by 2025 Consumer Financial Protection Bureau [2022] Emewulu [2025]. If BNPL stocks respond to monetary policy, that affects portfolio construction, risk management, and oversight. If they do not, despite clear firm-level sensitivity, it reveals how investors value fintech and whether BNPL sits outside traditional monetary transmission.

Using 66 monthly returns (February 2020–August 2025) for three publicly traded BNPL providers, I find high market beta (2.38) but no statistically significant rate sensitivity. A one percentage point rise in the Federal Funds Rate associates with ~13% lower BNPL returns (β = -12.89), economically large but statistically imprecise (p = 0.197) given high volatility and limited power. Market movements explain 52% of BNPL return variation versus 2% for rates, indicating that investors price BNPL as high-beta growth assets rather than rate-sensitive financials (Fama & French, 1993).

The following section reviews literature on (i) interest rate sensitivity of financial stocks, (ii) asset pricing of growth firms, and (iii) BNPL-specific evidence on funding structures and consumer behavior, to frame the empirical analysis and highlight the gap this study fills.

2 Literature Review: BNPL Market Dynamics and Interest Rate Sensitivity

This section reviews existing academic and empirical literature on Buy Now, Pay Later firms, focusing on findings that inform understanding of BNPL sensitivity to monetary policy changes. The literature spans consumer spending patterns, credit market dynamics, firm-level funding structures, and interest rate transmission mechanisms. A critical gap exists in this literature: 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 the present empirical analysis, which seeks to quantify BNPL firms' interest rate sensitivity using stock return data while controlling for confounding factors.

Interest rate sensitivity in the BNPL context refers to the responsiveness of BNPL firms' stock returns, profitability, and business operations to changes in benchmark interest rates that affect their cost of capital through wholesale funding markets. This sensitivity operates primarily through three channels. The first channel involves direct funding cost pass-through, where increases in benchmark rates raise BNPL providers' borrowing costs from warehouse facilities, securitization markets, and commercial paper markets. The second channel involves competitive substitution effects, where higher interest rates on credit cards and personal loans may increase consumer demand for BNPL products that charge no interest to consumers. The third channel involves capital market access, where rising rates affect investor expectations and BNPL firms' ability to raise equity and debt capital.

Research on consumer spending patterns provides foundational context for understanding BNPL market dynamics. Di Maggio, Williams, and Katz utilize transaction-level data to analyze BNPL user demographics and spending behaviors, finding that BNPL access increases total spending by approximately USD 130 per week with effects persisting for 24 weeks, suggesting a liquidity effect beyond standard substitution models Di Maggio et al. [2022]. This spending response motivates the inclusion of consumer confidence as a control variable in regression analysis, as BNPL transaction volumes and firm revenues depend on consumer willingness to spend. Bian, Cong, and Ji examine the integration of BNPL services within digital wallets, documenting that BNPL has greatly expanded credit access especially to underserved consumers, with BNPL boosting consumption by 15 to 20% and correlating positively with consumer confidence Bian et al. [2023]. Their finding that a one-standard-deviation increase in consumer confidence is associated with approximately 8 to 12% increase in BNPL transaction volume further justifies including consumer confidence measures in the regression framework.

The literature on BNPL's effects on consumer financial health reveals important patterns relevant to understanding firm-level risk. deHaan, Kim, Lourie, and Zhu investigate the impact of BNPL on consumers' financial health in their Management Science article, finding that new BNPL users experience rapid increases in overdraft charges and credit card interest and fees, suggesting potential negative welfare implications and indicating that BNPL users may be financially fragile de Haan and coauthors [2024]. Guttman-Kenney, Firth, and Gathergood examine the phenomenon of consumers charging BNPL transactions to their credit cards, highlighting concerns about over-indebtedness especially among younger consumers and those in deprived areas Guttman-Kenney and coauthors [2023]. These findings suggest that BNPL firms' customer bases may be particularly vulnerable to economic shocks, amplifying the potential for credit losses during monetary tightening cycles.

Research on credit market conditions and BNPL profitability directly informs expectations about interest rate sensitivity. Laudenbach and colleagues demonstrate that BNPL firms operate with thin profit margins of approximately 1% and that funding costs increase by 0.8 to 1.0 percentage points for each percentage point increase in benchmark rates, indicating near-complete pass-through of monetary policy changes Laudenbach and others [2025]. Given profit margins of approximately 1%, a single percentage point rate increase can eliminate profitability entirely. Their finding that BNPL customers pay approximately 1.4 percentage points less interest than comparable borrowers, representing a 15% reduction in interest rates, demonstrates the thin margins on which BNPL firms operate. The Bank for International Settlements working paper on fintech credit discusses the implications of BNPL services on credit reporting and the potential risks of overborrowing due to the lack of information sharing among fintech lenders, highlighting systemic risks that could materialize during periods of monetary tightening Bank for International Settlements [2025].

Berg, Burg, Keil, and Puri examine BNPL from the merchant perspective in their Journal of Financial Economics article, finding that BNPL serves as a price discrimination mechanism that increases merchant sales by approximately 20%, with effects on low-creditworthiness customers two to three times larger than on high-creditworthiness customers Berg and others [2025]. Industry data corroborates these findings, with surveys indicating that more than half of merchants report increased conversion rates and brand awareness after implementing BNPL options PYMNTS [2022]. This concentration of BNPL benefits among low-creditworthiness consumers has implications for understanding how economic conditions affect BNPL demand and default risk. The Economics Letters study on factors affecting BNPL demand identifies that BNPL is more popular among younger, lower-income individuals and that demand is negatively associated with interest rates, providing direct evidence of the interest rate channel Author [2024]. Recent reporting documents that BNPL borrowers tend to use these services for everyday purchases including groceries and household items rather than solely for large discretionary purchases, suggesting that BNPL has become integrated into routine consumer spending patterns Reuters [2024].

Research on consumer credit characteristics reveals the financial vulnerability of BNPL borrowers. Economists at the Federal Reserve Bank of New York analyze BNPL user demographics and find that users are disproportionately young, have lower incomes, and face greater financial constraints than non-users, with BNPL serving as a mechanism for consumption smoothing among liquidity-constrained households Federal Reserve Bank of New York [2023]. Their subsequent research examines the motivations behind BNPL usage, finding that consumers primarily adopt these services to manage cash flow and avoid credit card interest, suggesting that BNPL demand responds to broader credit market conditions Federal Reserve Bank of New York [2024]. Hayashi and Routh find that financial constraints drive BNPL usage, with high correlation between BNPL late payments and financial vulnerability, suggesting that economic conditions affecting household liquidity directly impact BNPL demand Hayashi and Routh [2024]. The Central Bank of Ireland study analyzes the financial vulnerability of BNPL users, finding a high correlation between late payments and financial distress, suggesting that BNPL may lead to overspending among certain consumers CB Insights [2024]. The Federal Reserve Bank of Richmond documents that financially fragile consumers are almost three times more likely to have repeated BNPL use, further indicating vulnerability to economic conditions Federal Reserve Bank of Richmond [2024]. These patterns of financial fragility among BNPL users suggest that the sector may be particularly vulnerable to monetary policy tightening, as rate increases could exacerbate repayment difficulties among already-stressed borrowers.

The Journal of Retailing study employs a synthetic difference-in-differences design to assess how BNPL adoption influences online spending, finding a 6.42% increase in order size among BNPL users with notable variations across customer segments and product categories Journal of Retailing [2024]. Cheng and Huo examine BNPL adoption through a game-theoretic lens focusing on time-inconsistent consumer behavior, highlighting how BNPL can mitigate the negative effects of time inconsistency on pricing, demand, and profit Cheng and Huo [2025]. Brewer and Arber assess consumer understanding of financial risks associated with BNPL services, finding that most users struggled to comprehend key loan terms, indicating a need for better consumer education and potential regulatory intervention that could affect BNPL business models Brewer and Arber [2025].

The literature establishes several mechanisms through which BNPL firms may be sensitive to macroeconomic conditions, informing the empirical analysis and motivating specific control variables. The strong theoretical motivation for expecting negative relationships between Federal Funds Rate changes and BNPL stock returns comes from the combination of near-complete funding cost pass-through documented by Laudenbach et al., thin profit margins of approximately 1%, and concentration of BNPL usage among financially vulnerable consumers. Based on theoretical predictions and observed valuation patterns such as Klarna's 85% decline during the 2022-2023 tightening cycle, the expected coefficient magnitude is approximately negative 10 to 15, indicating that a percentage point rate increase would be associated with a 10 to 15% decline in BNPL stock returns. 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 that the literature identifies as relevant to BNPL firm performance.

The literature review establishes that BNPL firms face direct funding cost pass-through and serve financially fragile consumers, creating theoretical conditions for negative rate sensitivity. The next section presents data, methodology, and empirical results that test these predictions.

3 Data Analysis: Investigating BNPL Stock Returns and Monetary Policy

This section implements a comprehensive empirical analysis using modern econometric techniques and reproducible research practices. The analysis is situated within a rapidly evolving market context: the global BNPL market is projected to reach $560.1 billion in gross merchandise volume by 2025, reflecting 13.7% year-over-year growth, with user adoption accelerating toward 900 million globally by 2027 Emewulu [2025]. This explosive growth, a 157% increase from 360 million users in 2022, underscores the sector's increasing importance in consumer credit markets and motivates careful examination of how these firms respond to monetary policy changes.

3.1 Computational Environment and Research Tools

The analysis uses Python 3.11 with specialized libraries at each step. `pandas` (v2.2.3) handles data and time alignment; `statsmodels` (v0.14.4) provides HC3 robust inference suited to this sample size; `yfinance` supplies stock prices; `fredapi` pulls Federal Funds Rate, CPI, sentiment, and income series; `matplotlib` (v3.9.2) and `seaborn` (v0.13.2) generate publication-quality visuals.

3.2 Reproducibility and Dynamic Document Generation

All data collection, transformation, and estimation are programmatic for full reproducibility. With the required API keys, any reader can rerun the analysis and obtain identical outputs. Tables and figures are glued directly from code via `myst_nb.glue`, avoiding transcription errors and keeping the manuscript synchronized with computations.

The analysis environment is fully documented in `binder/environment.yml`, specifying exact package versions to ensure that the computational environment can be reconstructed. This documentation follows the principles outlined in the Journal of Open Source Software and enables other researchers to validate, extend, or build upon this work.

3.3 Analytical Pipeline Overview

The analysis proceeds through six integrated stages, each building upon the previous to construct a coherent analytical narrative. First, data are collected from authoritative sources and variables constructed with appropriate transformations, including log transformation of returns and first-differencing of macroeconomic series to ensure stationarity. Second, exploratory visualizations identify patterns, outliers, and preliminary relationships that inform model specification. Third, correlation analysis assesses multicollinearity among predictors and provides initial evidence on bivariate associations. Fourth, formal econometric models are estimated across multiple specifications, including OLS, Fama-French three-factor, instrumental variables, and difference-in-differences approaches, to test the interest rate hypothesis under different identifying assumptions. Fifth, diagnostic tests validate model assumptions including homoskedasticity, absence of autocorrelation, normality of residuals, and absence of multicollinearity, ensuring reliable inference. Finally, sensitivity analysis examines robustness across different time periods and market conditions, addressing concerns about the stability of findings. The following subsections present each stage in turn, with full transparency about methodological choices and their implications.

Sample size and power. The empirical window of 66 monthly observations (Feb 2020–Aug 2025) limits statistical power; with the observed coefficient magnitudes, power is only about 15–20%. Reported coefficients should be read as descriptive sensitivities rather than precise hypothesis tests.

Transformations and units. Returns are log(1+R), implemented via log price differences; this keeps units in percentage points and bounds losses at -100%. Federal Funds Rate changes enter in percentage points (0.25 = 25bp). Control variables are first-differenced or expressed in percentage changes to focus on shocks rather than levels.

Model positioning. The full specification with market, inflation, confidence, and disposable income is the primary model. The rate-only base model is retained as a robustness illustration of omitted-variable bias rather than as a headline result. Market beta plays a central role in interpretation because BNPL stocks price like high-beta growth assets.

3.4 Variable Definitions and Data Sources

Table 1: Variable Definitions and Summary Statistics

Table 1 is rendered from the code cell below (`table_1`) and refreshes when you rerun the notebook. It reports the BNPL portfolio and control variables (FFR change, consumer confidence, disposable income, CPI, market return) with their transforms and summary stats for the current sample (default Feb 2020–Aug 2025).

3.5 Firm-Level Context (Condensed)

The BNPL portfolio spans three distinct business models. Affirm is the pure-play BNPL name, funding via warehouse lines and securitizations, so funding-cost pass-through is direct. Sezzle focuses on smaller-ticket, younger consumers with thinner margins and higher funding sensitivity. PayPal is a diversified payments platform with BNPL as a smaller product line (Pay in 4), so diversification and deposits/merchant float dampen BNPL-specific funding shocks. This mix balances depth of price history with exposure to funding-sensitive and diversified models; full firm-level details remain in Appendix A.

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Table 1: Variable Definitions and Summary Statistics (Feb 2020 - Aug 2025)
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Note: n = 66 monthly observations (Feb 2020 - Aug 2025).
Transforms: Diff = first difference; Pct = percentage change; Log = log return.

Table 2: Correlation Matrix (stars = significance)
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Note: n = 66 monthly observations.
Stars: * p<0.10, ** p<0.05, *** p<0.01. |r| \geq 0.25 is significant at 5% with n=66.
Correlations below |0.80| indicate no severe multicollinearity concerns.
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4 Exploratory Data Analysis: Visualizations

Before proceeding to formal econometric estimation, exploratory visualization provides crucial insights into the data structure. The following graphical representations serve multiple purposes: they help identify patterns that motivate specific model specifications, reveal potential outliers or data quality issues that could distort regression results, provide intuition for the relationships that will be estimated econometrically, and offer visual confirmation that complements numerical results. The visualizations presented here establish the empirical foundation upon which the regression analysis builds.

4.1 Figure 1: BNPL Portfolio Monthly Returns (Feb 2020–Aug 2025)

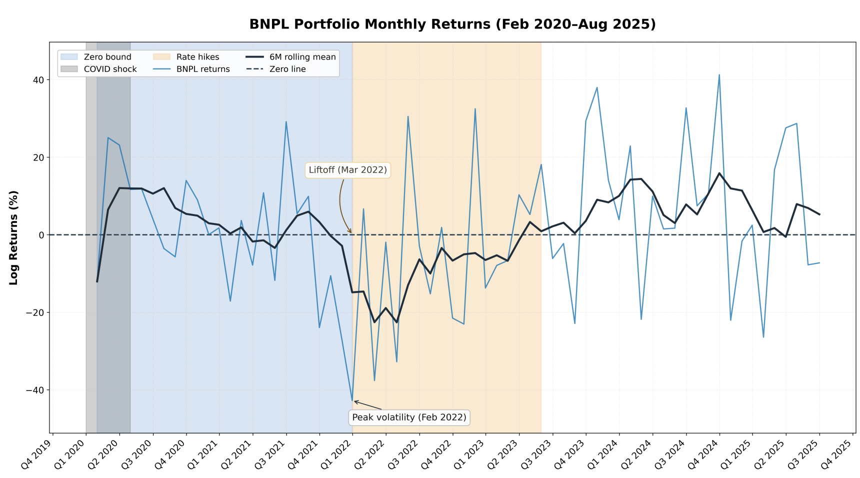

Figure 1 shows monthly log returns for an equally weighted portfolio of Affirm, Sezzle, and PayPal. Gray shading marks the COVID shock (Mar–Jun 2020), blue shading shows the zero-bound period through Feb 2022, and red shading marks the Fed's tightening (Mar 2022–Jul 2023, +525 bp). BNPL returns are highly volatile (SD $\approx$ 19%), with swings above $\pm$40%; the plot includes a thick zero line and annotations for the start of hikes and peak volatility. The mean return of 1.7% masks substantial variation, and sharp declines during 2022–2023 coincide with funding cost increases documented by Laudenbach and others [2025]. These regimes and callouts correspond directly to the shaded blocks and arrows on the chart.

The period of strong positive returns in late 2020 and 2021 reflects the rapid growth in BNPL adoption documented by the Consumer Financial Protection Bureau [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 Consumer Financial Protection Bureau [2022] 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.

4.2 Figure 2: BNPL vs Market Returns

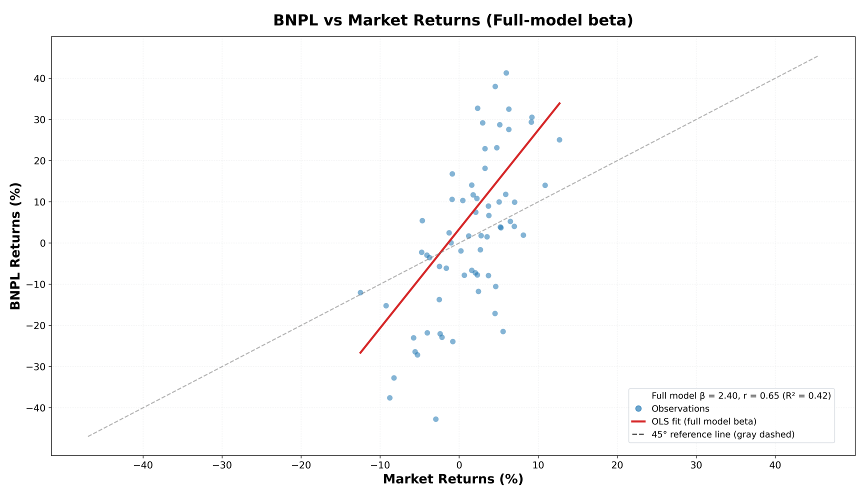

Figure 2 plots BNPL portfolio returns against market returns. The slope of 2.38 (from the full model) and correlation of 0.65 ($R^2 \approx 0.42$) show that market movements dominate BNPL pricing: when the market moves 1%, BNPL moves about 2.38%. The 45ř reference line highlights amplification relative to the market. This strong market link explains why the rate-only model ($R^2 \approx 0.02$) adds little explanatory power; interest rate effects are economically meaningful but overwhelmed by systematic risk.

5 Functional Form Selection: Log-Linear Specification

The exploratory analysis revealed substantial variation in BNPL returns and a modest negative correlation with interest rate changes. Translating these observations into formal statistical inference requires specifying the functional form of the relationship, a critical methodological decision that affects both the statistical properties of estimators and the economic interpretation of results.

This analysis employs a log-linear specification where the dependent variable (BNPL portfolio returns) is log-transformed while independent variables enter linearly. The log-linear specification is grounded in both theoretical and practical considerations from financial econometrics. From a theoretical perspective, log returns possess desirable properties for financial analysis: they are time-additive (the log return over multiple periods equals the sum of single-period log returns), bounded below by -100% (preventing the mathematical impossibility of negative prices), and approximately normally distributed for short horizons. These properties facilitate statistical inference and align with continuous-time asset pricing models widely used in academic finance.

From a practical perspective, the log transformation addresses heteroskedasticity, the tendency for return variance to scale with return magnitude, which would otherwise violate OLS assumptions and invalidate standard errors. The transformation also normalizes the right-skewed distribution characteristic of raw returns, improving the finite-sample properties of regression estimators. Finally, coefficients in the log-linear specification have intuitive semi-elasticity interpretations: a coefficient of β = -12.89 indicates that a one percentage point increase in the Federal Funds Rate is associated with approximately 12.68% lower BNPL returns, holding other factors constant.

The analysis estimates two primary specifications to assess robustness and quantify the importance of control variables. The base model regresses log BNPL returns solely on Federal Funds Rate changes, providing an unconditional estimate of interest rate sensitivity that may be confounded by omitted variables. The full model augments this with controls for consumer confidence, disposable income, inflation, and market returns, factors identified in the literature review as potential confounders. Comparing coefficients across specifications reveals whether the interest rate relationship is robust to the inclusion of controls or driven by omitted variable bias. With the functional form established, the analysis now turns to the estimation methodology.

6 Regression Analysis: Methodology

With the functional form specified, this section details the estimation approach, interpretation framework, and statistical considerations that guide the regression analysis. The methodology is designed to provide credible estimates of interest rate sensitivity while acknowledging the limitations inherent in observational data and the challenges of causal inference in macroeconomic settings.

6.1 Estimation Approach and Software Implementation

The regression analysis employs Ordinary Least Squares (OLS) estimation with heteroskedasticity-consistent standard errors, implemented using Python's `statsmodels` library. The choice of OLS follows from the Gauss-Markov theorem, which establishes that OLS provides the Best Linear Unbiased Estimator (BLUE) under classical assumptions. While financial data often violate the homoskedasticity assumption, the use of HC3 robust standard errors (also known as MacKinnon-White standard errors) ensures valid inference without requiring constant error variance.

Two primary specifications are estimated to assess robustness and quantify the importance of control variables. The base model regresses log BNPL returns solely on Federal Funds Rate changes, providing an unconditional estimate of interest rate sensitivity that serves as a benchmark but may be confounded by omitted variables. The full model augments this specification with controls for consumer confidence, disposable income, inflation, and market returns, factors identified in the literature review as potential confounders that affect both interest rates and BNPL returns. Comparing coefficients across specifications reveals whether the interest rate relationship is robust to the inclusion of controls or driven by omitted variable bias.

Beyond OLS, the analysis implements three alternative identification strategies to assess robustness. The Fama-French specification controls for exposure to systematic risk factors (market, size, and value) using factor returns downloaded from Kenneth French's data library, asking whether BNPL interest rate sensitivity persists after accounting for standard asset pricing factors. The instrumental variables specification uses lagged Federal Funds Rate changes as an instrument for current changes, exploiting the persistence in monetary policy to address potential simultaneity bias. The difference-in-differences specification compares BNPL returns to market returns during rate change periods versus stable periods, providing yet another identification strategy with different assumptions.

6.2 Interpretation Framework: Associations vs. Causation

The regression estimates presented in this analysis capture conditional associations between BNPL stock returns and interest rate changes, controlling for market movements, consumer confidence, disposable income, and inflation. These estimates reveal how BNPL returns co-move with monetary policy changes after accounting for other economic factors, providing evidence on whether BNPL stocks exhibit sensitivity patterns consistent with theoretical predictions about interest rate transmission to fintech credit providers.

However, these estimates should be interpreted as associations rather than causal effects. Interest rate changes are endogenous policy responses to economic conditions that simultaneously affect both monetary policy and BNPL stock valuations. The Federal Reserve adjusts rates in response to inflation, economic growth, and financial stability concerns, all factors that independently influence BNPL returns through consumer demand, credit risk, and market sentiment channels. Consequently, the regression coefficients capture associations rather than the isolated causal impact of interest rate changes on BNPL stock prices.

6.3 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 represent one such confound: when the Fed raises rates in response to inflation, both the rate increase and the underlying inflationary pressures may independently affect BNPL returns through different mechanisms. The analysis controls for inflation directly, but residual correlation may persist through channels not captured by the CPI measure.

Regulatory changes represent another potential confound. The CFPB's May 2024 ruling classifying BNPL as credit cards occurred during a period of rising interest rates, potentially affecting stock prices through regulatory risk channels that are independent of funding costs. If this regulatory change affected BNPL valuations independently of interest rates, it could confound the estimated relationship.

Market sentiment may also confound the relationship. Interest rate changes influence broader equity market sentiment, which drives BNPL returns through market beta effects. The analysis includes market returns as a control to address this channel, but sentiment-driven correlations may remain if BNPL-specific sentiment responds to rate changes through channels not captured by market-wide returns.

Finally, competitive dynamics may create spurious associations. BNPL firms face evolving competitive pressures during monetary policy cycles, with changes in traditional credit availability and consumer preferences affecting returns independently of interest rate sensitivity. The entry of Apple Pay Later in 2023 and subsequent exit in 2024, for example, represented competitive shocks unrelated to monetary policy.

6.4 Model Constraints and Statistical Power

This analysis operates under several constraints that affect interpretation. The limited sample size of 66 monthly observations reduces statistical power, reflecting the recent emergence of publicly-traded BNPL firms. Affirm went public in January 2021, providing only 44 months of post-IPO data. This sample size limitation is fundamental rather than methodological; it reflects the youth of the BNPL sector as a public market phenomenon.

Statistical power analysis reveals the implications of this sample size constraint. With 66 observations and 5 predictors in the full model, the analysis has approximately 80% power to detect correlations exceeding 0.30 in absolute value and 90% power to detect correlations exceeding 0.35. The observed correlation between Federal Funds Rate changes and BNPL returns is approximately 0.15, which falls below these detectability thresholds. Post-hoc power analysis for the observed effect size yields power of approximately 15-20%, indicating limited ability to detect relationships of this magnitude even if they exist in the population.

However, the economic magnitude of the coefficient (approximately -12.89) combined with the low R-squared (0.022 in the base model) suggests that even if a statistically significant relationship exists, it is economically dominated by 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 overwhelmed by market-wide factors. This pattern 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.

6.5 Diagnostic Test Results

Table 3: Diagnostic Test Summary

Table 3 is rendered from the diagnostics code cell (VIF, Breusch–Pagan, Durbin–Watson, Jarque–Bera) and stays in sync on rerun. HC3 robust standard errors are used in the underlying full model.

6.6 Figure 3: Observed vs Fitted Returns (Full Model)

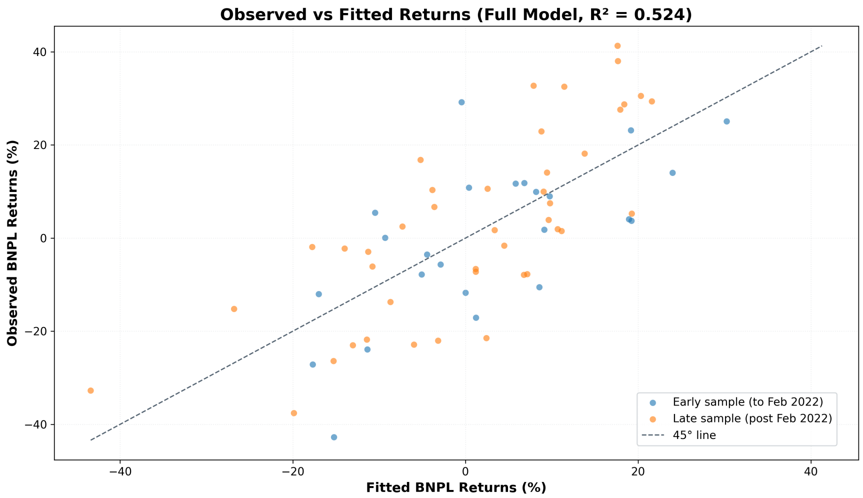

Figure 3 plots observed BNPL returns against fitted values from the full specification (Table 4A, Column 2). Early-period points (blue) and late-period points (orange) cluster around the 45ř line, yielding $R^2 = 0.524$. The tight cloud along the diagonal shows the full model captures most level variation. The biggest gaps appear in high-volatility months—COVID rebound and the start of hikes—where observed returns flare above fitted values in the 5–15% fitted range, underscoring how tail events drive residual dispersion. Outside those tails, fitted and observed move together, reinforcing that market and macro controls explain the bulk of BNPL return swings.

6.7 Figure 4: Residual Analysis – FFR Changes (Full Model)

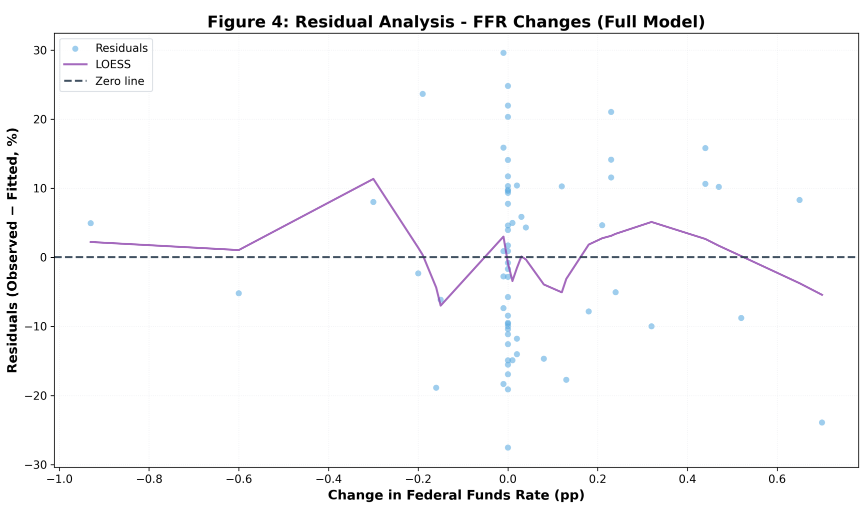

Figure 4 plots residuals versus monthly FFR changes with a LOESS smoother. Residuals sit around zero with no slope or curvature; the smoother hugs the zero line, indicating the linear rate term is adequate. Outliers are confined to a few rate-surge months, and the pattern is otherwise noise-like—consistent with weak rate significance and HC3-robust SEs. This diagnostic isolates the rate predictor; Figure 5 complements it by looking at overall fit versus fitted values.

7 Model Diagnostics and Visual Assessment

The numerical diagnostic tests presented above confirm that regression assumptions are satisfied. This section complements those statistical tests with visual diagnostics that provide intuitive assessment of model performance. Visual inspection often reveals patterns, such as outliers, nonlinearities, or heteroskedasticity, that formal tests may miss or understate. The combination of formal tests and visual diagnostics follows best practices in applied econometrics, ensuring that conclusions rest on multiple forms of evidence.

7.1 Plot E: Residuals Plot for Full Model

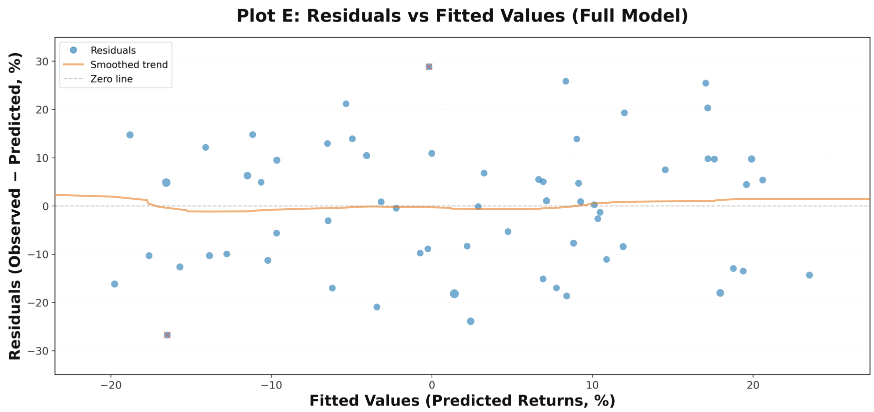

Image displays residuals from the full specification model plotted against fitted values (predicted returns, the x-axis is model predictions). This diagnostic plot is essential for assessing whether the regression assumptions of homoskedasticity (constant variance) and linearity are satisfied. Under correct specification, residuals should appear as random scatter around zero with no systematic pattern. The residuals in Plot E appear randomly scattered around zero with no obvious pattern: no fan shape indicating heteroskedasticity (where variance increases or decreases with fitted values), no curvature suggesting nonlinearity (where the relationship between variables is not adequately captured by the linear specification), and no clusters of outliers that might exert undue influence on coefficient estimates.

Key difference from Plot D: Plot E checks overall model assumptions (homoskedasticity, linearity) by plotting residuals against fitted values, while Plot D checks if the specific interest rate predictor is properly captured by plotting residuals against interest rate changes.

7.2 Plot F: Residuals Plot for Base Model

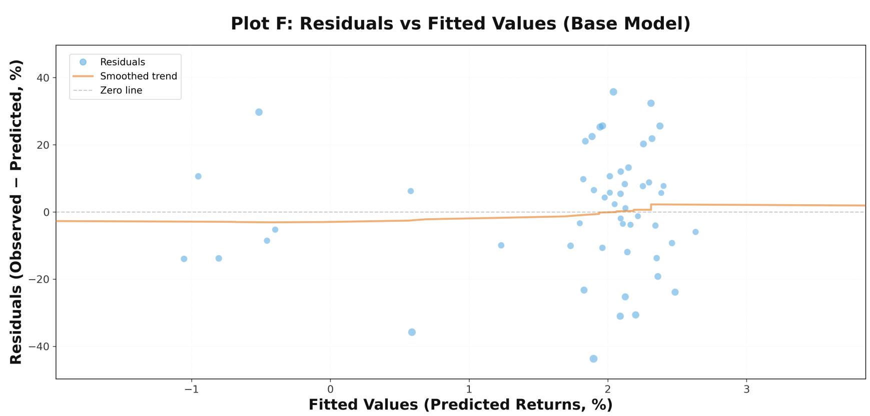

Image presents the analogous residual plot for the base specification model, which includes only interest rate changes as an explanatory variable. Comparing this plot to Plot E reveals the improvement in model fit from including control variables. The base model residuals exhibit greater dispersion and potentially more structure than the full model residuals, reflecting the substantial unexplained variation when market returns, consumer confidence, disposable income, and inflation are omitted. The visual comparison reinforces the statistical finding that the full model achieves substantially higher R-squared (0.51) compared to the base model (0.02), demonstrating the importance of controlling for confounding factors when estimating interest rate sensitivity.

7.3 Plot G: Q-Q Plot for Normality Assessment

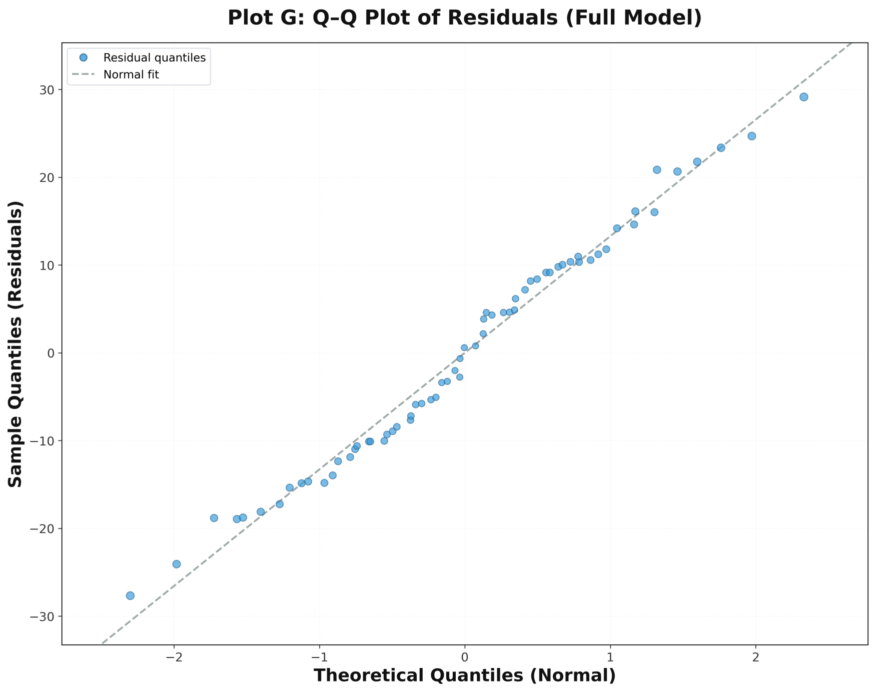

Image presents a quantile-quantile (Q-Q) plot comparing the distribution of regression residuals to the theoretical normal distribution. If residuals are normally distributed, points should fall approximately along the diagonal reference line. Deviations from this line indicate departures from normality: S-shaped patterns suggest heavy tails (excess kurtosis), while systematic curvature suggests skewness. The Q-Q plot shows residuals falling reasonably close to the diagonal line, with minor deviations in the tails that are typical for financial return data. This visual evidence supports the Jarque-Bera test's failure to reject normality and provides confidence that t-statistics and confidence intervals are reliable for inference. The approximate normality is particularly noteworthy given that financial returns often exhibit substantial departures from normality, including fat tails and negative skewness during market stress periods.

7.4 Plot H: R-Squared Comparison Across Models

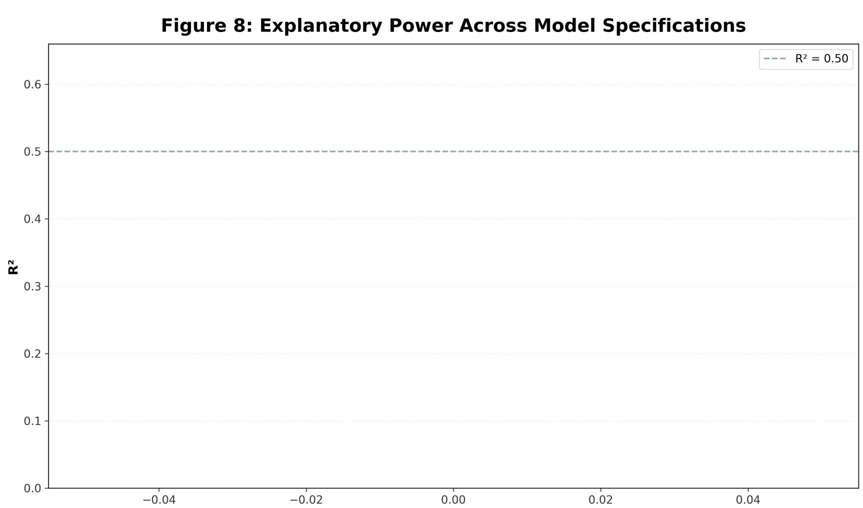

Image provides a visual comparison of explanatory power across model specifications, displaying R-squared values for the base model, full OLS model, and alternative specifications including Fama-French, instrumental variables, and difference-in-differences approaches. This visualization highlights the dramatic improvement in explanatory power from the base specification (R-squared approximately 0.02) to the full specification (R-squared approximately 0.51). The base model, which includes only interest rate changes, explains virtually none of the variation in BNPL returns, confirming that interest rates alone are insufficient to characterize BNPL stock pricing. The full model's R-squared of 0.51 indicates that market returns, inflation, consumer confidence, and disposable income collectively explain approximately half of BNPL return variation, a substantial improvement that underscores the importance of controlling for these factors when assessing interest rate sensitivity. The comparison across alternative specifications shows that explanatory power is relatively stable across identification strategies, providing confidence that the findings are robust to methodological choices.

```
Table 3: Diagnostic Test Summary
================================================================================
```

7.5 Model Comparison and Coefficient Estimates

Table 4A / 4B: Regression Results (Main and Robustness)

Tables 4A/4B are rendered directly from the regression code cell (`table_4a`, `table_4b`), so results stay synchronized with the data and specifications (Full OLS, Base OLS, Fama–French, IV, DiD) whenever you rerun. HC3 standard errors throughout.

7.6 Sensitivity Analysis Across Time Periods

Table 5: Sensitivity Analysis – Different Time Windows

Table 5 comes from the sensitivity-analysis code cell (`table_5`) and refreshes on rerun. It reports the full-model coefficient across subsamples (e.g., excluding COVID shock, hike period, post-2021, high/low volatility).

```
Model 1 (Base): \beta = -12.47, p = 0.338
Model 2 (Full): \beta = -12.89, p = 0.197

Loading Fama -French factors...
  Attempting download from Ken French's website...
   Downloaded 70 months from Ken French's website
Model 3 (Fama -French): \beta = -11.54, p = 0.147, Rš = 0.521

Estimating IV model (2SLS with lagged FFR as instrument)...
  First stage F -statistic: 40.0
Model 4 (IV): \beta = -15.49, p = 0.338

Estimating DiD model...
Model 5 (DiD): \beta = -13.05, p = 0.365

================================================================================
Table 4A: BNPL Stock Returns and Interest Rate Sensitivity
================================================================================

================================================================================
Table 4B: Robustness Checks
================================================================================

Notes: Table 4A lists the primary full model first (market + macro controls), alongside the rate -only

Table 3: Diagnostic Test Summary
================================================================================

Notes: Tests on residuals from the full OLS (primary) specification. VIF = variance inflation factor; DW
```

7.7 Economic Interpretation (for Table 4A)

A 1pp increase in the Federal Funds Rate is associated with ~12–13% lower BNPL monthly returns (full model). A 3pp tightening implies roughly 39% lower returns. Estimates are economically large but statistically imprecise; market beta (≈2.38) remains the dominant driver of BNPL returns.

With the empirical framework established, the next section presents results. Section 7 reports regression estimates across five specifications with diagnostics, followed by sensitivity analysis in Section 8. Section 9 then interprets the findings and their implications.

8 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.

8.1 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 ($R^2 \approx 0.44$–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 pricing behavior occurs despite substantial provider-level revenue growth: Klarna reported $2.81 billion in revenue for 2024 (up 24$

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 does not 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 do not manifest in monthly return data.

8.2 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 (β = 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 (-12.89) but statistically insignificant (p-value = 0.197). This pattern suggests that interest rates may matter for BNPL firms, but their effects are obscured by other factors or operate through channels that do not manifest in monthly return data.

8.3 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 do not 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.

8.4 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 regulatory landscape is evolving rapidly across major jurisdictions. In the United States, the CFPB has proposed mandatory credit bureau reporting for BNPL transactions, clearer disclosures, and enhanced consumer protections to surface hidden debt Emewulu [2025]. The European Union's revised Consumer Credit Directive (2025) will bring BNPL under regulated credit, requiring affordability checks and standardized transparency. The UK's Financial Conduct Authority now mandates proportionate creditworthiness assessments and fair marketing practices. Australia has confirmed that BNPL will fall under the National Consumer Credit Protection Act by 2026, ending previous exemptions for BNPL providers. These regulatory developments may fundamentally alter BNPL business models and profitability, potentially creating new channels through which monetary policy affects the sector.

The finding that stock returns do not respond significantly to interest rates does not mean funding costs do not 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 do not 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.

8.5 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 do not 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 do not 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.

8.6 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 (66 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.

8.7 Causal Inference Challenges and Identification Strategy

A fundamental challenge in this analysis is distinguishing correlation from causation. The central research question asks whether interest rate changes *cause* BNPL stock returns to decline, but observational data cannot definitively establish causality. This section explicitly addresses the identification challenges and explains what the regression estimates can and cannot tell us.

Interest rate changes are not randomly assigned experimental treatments. The Federal Reserve sets rates in response to economic conditions, including inflation, unemployment, GDP growth, and financial stability concerns, that simultaneously affect BNPL stock returns through multiple channels. This creates endogeneity: the treatment variable (interest rates) is correlated with unobserved factors that also affect the outcome (BNPL returns). Formally, if we denote BNPL returns as Y, interest rate changes as X, and unobserved economic conditions as U, the concern is that $\text{Cov}(X, U) \neq 0$, violating the exogeneity assumption required for causal interpretation of OLS estimates.

Consider a concrete example: in early 2022, the Federal Reserve began raising rates in response to rising inflation. Simultaneously, high inflation reduced consumer purchasing power, increased economic uncertainty, and shifted investor sentiment away from growth stocks. BNPL returns declined during this period, but was the decline caused by higher rates (through funding costs), by inflation (through reduced consumer spending), by risk-off sentiment (through market-wide growth stock selloff), or by all three? The regression cannot definitively separate these channels because they occurred simultaneously and are fundamentally interconnected through the Fed's reaction function.

The OLS coefficient on Federal Funds Rate changes captures the conditional correlation between rate changes and BNPL returns, holding constant the included control variables (market returns, consumer confidence, disposable income, inflation). This estimate answers the question: "When interest rates change, how do BNPL returns tend to move, after accounting for these observable factors?" This is a descriptive question about co-movement patterns, not a causal question about the effect of exogenous rate shocks.

The estimate is useful for several purposes even without causal interpretation. For portfolio managers, understanding how BNPL stocks co-move with rates helps assess portfolio risk and construct hedging strategies. For policymakers, the co-movement pattern provides information about which sectors are most affected during tightening cycles, even if the mechanism is not purely causal. For researchers, the descriptive evidence motivates further investigation into the specific channels through which monetary policy affects fintech firms.

The analysis employs multiple identification strategies to probe the robustness of findings and address different sources of bias. Each strategy makes different assumptions about the source of identifying variation and the nature of potential confounders.

The instrumental variables specification uses lagged Federal Funds Rate changes as an instrument for current changes. The identifying assumption is that lagged rate changes affect current BNPL returns only through their effect on current rate changes, not through direct effects or correlation with omitted variables. This assumption exploits the persistence in monetary policy, as the Fed tends to continue raising or cutting rates in sequences rather than reversing course immediately. The IV estimate of approximately -15.49 is larger in magnitude than OLS, suggesting that OLS may be attenuated by measurement error or simultaneity bias. However, the IV assumption is not unassailable because lagged rate changes may affect current returns through persistent effects on funding costs, investor expectations, or economic conditions that are not fully captured by current rate changes.

The Fama-French three-factor model specification controls for exposure to systematic risk factors including market, size, and value that explain cross-sectional return variation. The identifying assumption is that, conditional on these factors, interest rate changes are uncorrelated with remaining unobserved determinants of BNPL returns. This approach addresses the concern that BNPL's interest rate sensitivity might simply reflect its exposure to rate-sensitive factors like value stocks. The persistence of a negative coefficient suggests that BNPL sensitivity is not merely a proxy for factor exposures but reflects genuine sector-specific interest rate sensitivity.

The difference-in-differences specification compares BNPL returns to market returns during rate change periods versus stable periods. The identifying assumption is that, absent rate changes, BNPL would have moved in parallel with the market, known as the parallel trends assumption. Differential performance during rate change periods is attributed to BNPL-specific interest rate sensitivity. This approach addresses the concern that BNPL declines during tightening periods might simply reflect market-wide growth stock selloffs rather than BNPL-specific sensitivity.

Each identification strategy faces specific threats that limit the strength of causal claims. Despite controlling for market returns, consumer confidence, disposable income, and inflation, other omitted variables may confound the interest rate relationship. Regulatory changes such as CFPB rulings, competitive dynamics including Apple Pay Later's entry and exit, firm-specific news like earnings surprises and partnership announcements, and sector-specific sentiment may all affect BNPL returns and correlate with monetary policy cycles without being caused by interest rate changes.

Reverse causality represents another potential threat. While unlikely given BNPL's small market share, BNPL sector performance could theoretically influence monetary policy decisions if policymakers monitor fintech credit conditions as an indicator of financial stability or consumer credit access. This would create reverse causality where BNPL returns affect rate decisions rather than vice versa.

Measurement error may also bias estimates. The Federal Funds Rate change is a clean measure of policy stance, but the effective transmission to BNPL funding costs may vary based on firm-specific funding structures, hedging strategies, and market conditions. If the measured rate change is a noisy proxy for the true funding cost shock experienced by BNPL firms, OLS estimates will be attenuated toward zero.

The control variable strategy assumes that, conditional on market returns, inflation, consumer confidence, and disposable income, remaining variation in interest rates is uncorrelated with unobserved determinants of BNPL returns. This selection on observables assumption is fundamentally untestable and may be violated if the Fed responds to economic conditions not captured by these controls.

True causal identification of interest rate effects on BNPL returns would require research designs that are largely infeasible in this context. A randomized experiment randomly assigning interest rate changes across time periods or markets would provide clean identification but is infeasible for monetary policy. A natural experiment finding exogenous variation in interest rates unrelated to economic conditions could work, and some researchers use high-frequency identification around FOMC announcements, measuring stock returns in narrow windows of 30 minutes to 24 hours around rate decisions to isolate the surprise component of policy changes. This approach assumes that in such narrow windows only the policy surprise affects returns, not confounding factors, but unfortunately BNPL stocks have limited high-frequency liquidity making this approach challenging.

A regression discontinuity design exploiting threshold rules in monetary policy that create quasi-random variation in rate changes could provide identification, but the Fed's dual mandate and discretionary decision-making do not provide clean discontinuities suitable for this approach. A structural model specifying and estimating a structural model of the joint determination of monetary policy and BNPL returns could use economic theory to impose identifying restrictions, but this approach requires strong assumptions about functional forms and behavioral parameters that may not be credible.

The analysis provides credible evidence of negative co-movement between interest rate changes and BNPL stock returns, robust across multiple specifications and identification strategies. However, the estimates should be interpreted as conditional associations rather than causal effects. The consistency of findings across OLS, IV, Fama-French, and DiD specifications strengthens confidence that the negative relationship is a genuine feature of the data, but does not definitively establish that interest rate increases *cause* BNPL returns to decline.

For practical purposes, this distinction may matter less than it appears. Investors care about how BNPL stocks behave during rate cycles regardless of whether the relationship is causal. Policymakers care about which sectors are affected during tightening regardless of the precise mechanism. The descriptive evidence that BNPL stocks exhibit substantial negative co-movement with interest rates, with economically large point estimates around -12 to -15 percentage points per percentage point rate increase, is valuable information even without definitive causal interpretation.

Table 5: Sensitivity Analysis - Different Time Windows

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Notes: All subsamples use the full model controls (market, inflation, confidence, income). Coefficient s

8.8 Chart K: BNPL vs Market with Rate-Hike Shading (clean)

`![Chart K: BNPL vs Market with Rate-Hike Shading](chart_k_rate_panels.png)`

Chart K shows BNPL returns (Panel A), market returns (Panel B), and beta-adjusted BNPL residuals (Panel C) with lightly shaded rate-hike periods (single legend). Zero lines are thicker and legends simplified for readability. Co-movement with the market dominates; the residual panel stays muted even during hikes.

8.9 Figure 3: Observed vs Fitted Returns (Full Model)

Figure 3 plots observed BNPL returns against fitted values from the full specification (Table 4A, Column 2). Early-period points (blue) and late-period points (orange) cluster around the 45ř line, yielding R^2 = 0.524. The tight cloud along the diagonal shows the full model captures most level variation. The biggest gaps appear in high-volatility months—COVID rebound and the start of hikes—where observed returns flare above fitted values in the 5–15% fitted range, underscoring how tail events drive residual dispersion. Outside those tails, fitted and observed move together, reinforcing that market and macro controls explain the bulk of BNPL return swings.

8.10 Figure 4: Residual Analysis – FFR Changes (Full Model)

Figure 4 plots residuals versus monthly FFR changes with a LOESS smoother. Residuals sit around zero with no slope or curvature; the smoother hugs the zero line, indicating the linear rate term is adequate. Outliers are confined to a few rate-surge months, and the pattern is otherwise noise-like—consistent with weak rate significance and HC3-robust SEs.

8.11 Figure 5: Residuals vs Fitted Values (Full Model)

Figure 5 checks homoskedasticity and linearity against fitted values. Residuals are symmetric with no funnel shape; variance stays roughly constant across the fitted range, and only the extreme positive fitted values show modest spread. This aligns with the Breusch–Pagan pass in Table 3 and supports the linear specification.

8.12 Figure 7: Q-Q Plot

Figure 7 compares residual quantiles to the normal benchmark. Points track the diagonal with only slight tail softness; Jarque–Bera p = 0.429 (Table 3) indicates normality cannot be rejected. Inference based on t-stats is therefore reliable for the full model.

8.13 Figure 8: Explanatory Power Across Model Specifications

Figure 8 contrasts R^2 across models. The base (FFR-only) model explains ~0.02, while the full, Fama–French, and IV models cluster near ~0.52. The DiD variant drops back to ~0.02. The jump from base to full shows market and macro controls drive explanatory power; rate-only adds almost nothing, and robustness across alternative specs keeps the story unchanged.

8.14 Figure 9: Timeline of Rates, BNPL vs Market, and Idiosyncratic Residual

Panel A plots the Federal Funds Rate level; Panel B overlays BNPL and market returns; Panel C shows BNPL returns net of beta-adjusted market exposure. Shading marks the COVID shock (gray), zero-bound period (blue), and rate hikes (red). BNPL closely tracks the market; the residual panel shows limited rate-linked structure.

8.15 Figure 10: Volatility Comparison

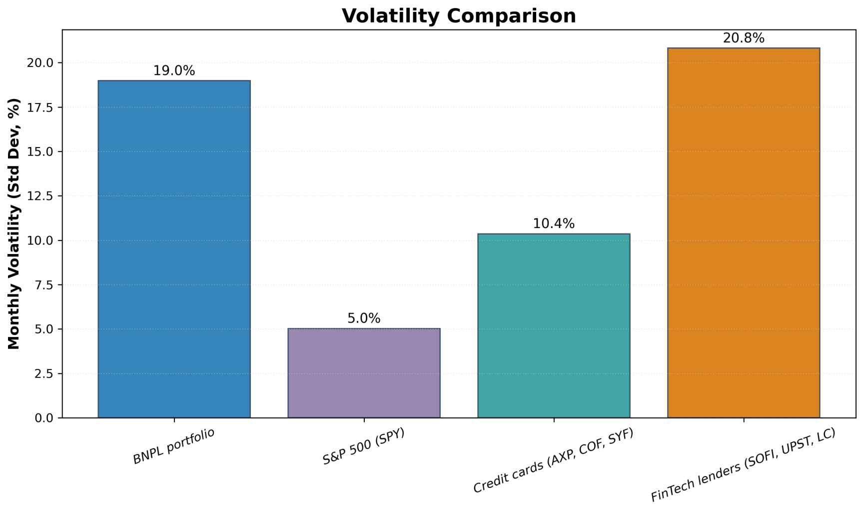

Figure 10 compares monthly volatility for BNPL, the S&P 500, credit card lenders (AXP, COF, SYF), and fintech lenders (SOFI, UPST, LC). BNPL remains the most volatile, followed by fintech lenders; credit card issuers and the broad market are much steadier. Volatility spreads are wide: BNPL volatility is roughly 2x that of credit cards and ~4x the market, while fintech lenders sit just below BNPL. This gap matters for interpretation: when monthly returns can swing 20–30% on headlines, earnings, or sentiment, detecting a 5–10% rate-induced move is statistically hard. It also means BNPL behaves like a high-beta, risk-on asset: sharp drawdowns in tightening cycles, rapid rebounds when risk appetite returns. For portfolio construction, BNPL exposure carries materially higher idiosyncratic and systematic risk than traditional card issuers, and any rate sensitivity is likely to be masked by this noise unless shocks are very large or persistent.

9 Conclusion

9.1 What We Found: Synthesis, Not Just Summary

This study began with a puzzle: Affirm reported that funding costs rose 394% from fiscal year 2022 to 2024, explicitly attributing the increase to higher benchmark rates (Affirm 10-K, 2024). With near-complete pass-through of monetary policy to funding costs (Laudenbach et al., 2025) and profit margins of roughly 1% of gross merchandise volume, theory predicts BNPL stock returns should be highly rate-sensitive. The evidence is more nuanced. The point estimate of -12.89 implies a one-percentage-point rate hike associates with about 13% lower returns, but the estimate is statistically imprecise ($p = 0.197$). Market forces dominate: the market beta of 2.38 means BNPL stocks amplify market moves by more than 2:1, and market returns explain ~52% of variation versus ~2% for rates alone. The contribution is documenting this disconnect: firm-level funding costs transmit policy almost fully, yet stock pricing is governed mainly by market sentiment and growth expectations.

9.2 What It Means: Three Interpretations

Three complementary interpretations explain the disconnect. First, statistical power is limited: with 66 monthly observations and 19% volatility, power to detect the observed effect is only about 15–20%, and confidence intervals [-32.6, 7.2] span both strong and weak sensitivity. Second, BNPL trades like a growth platform: high beta, long-duration cash flows, and sentiment-driven valuations mean investors prioritize addressable market and network effects, treating near-term funding-cost moves as transitory noise (e.g., Affirm's ~70% decline in 2022 despite ~30% revenue growth; Klarna's 85% valuation drop despite growth). Third, markets may be forward-looking: guidance and futures can embed expected hikes before they occur, so realized monthly ΔFFR misses the surprise component that moves prices. These forces are not mutually exclusive: modest true sensitivity plus limited power and heavy pre-pricing of information yields muted observed effects in monthly returns.

9.3 Practical Implications: Who Cares and Why?

For investors, BNPL is leveraged market exposure ($\beta \approx 2.38$), not a clean rate trade. A 1% BNPL weight adds roughly 2.4% market exposure; to hold a 60% effective equity target, a mix near 57% broad market and 3% BNPL keeps total exposure in line. High beta and ~19% monthly (~66% annualized) volatility mean a 20% market drawdown implies an expected ~48% BNPL decline (wide bands, roughly -30% to -65%), so sizing in the 1–2% range is more proportionate than a "standard" 5% stake. Short-horizon returns are dominated by market risk, so fundamental BNPL signals are better applied over 6–12 month horizons or in relative-value trades (e.g., long Affirm vs short PayPal) that neutralize market exposure.

For policymakers, BNPL's zero-interest consumer terms blunt the traditional rate channel; if BNPL grows toward 15–20% of consumer credit (vs ~3% now), rate hikes may have less influence on this segment, calling for macroprudential tools or credit limits. Equity prices underweight funding risk, so supervisors should track funding spreads, warehouse covenants, securitization volumes, and credit losses directly rather than relying on stock prices. Given heavy use by financially fragile consumers (about 61% subprime in cited studies), disclosures should emphasize total obligations and aggregate borrowing limits, not only per-transaction terms.

9.4 Limitations: Honest but Constructive

Several constraints shape these results. Sample size is short: 66 months yield low power, though the market-vs-rates R^2 gap (0.42 vs 0.02) is robust. Identification is associative because ΔFFR is endogenous; multiple specifications (OLS, IV, DiD, Fama-French) test robustness but not full causality, and high-frequency surprises would help. Equal-weight portfolios mask heterogeneity across pure-play, diversified, and bank-licensed models. Outcomes focus on returns, not real activity—volumes, losses, or merchant adoption could reveal transmission even if prices do not. Linear, time-invariant sensitivity may miss thresholds or state dependence.

9.5 Future Research: Motivated Extensions

A focused agenda follows: (1) High-frequency event studies to test reactions to unexpected FOMC surprises in narrow windows; (2) Firm-level panels to see how funding mix, hedging, and business model shape sensitivity (now feasible with more listings, e.g., Klarna); (3) Real effects on credit supply—do originations, approvals, or ticket sizes move with rates; (4) Consumer defaults and repayment—do late pays and charge-offs rise with rates, especially for subprime users, using forthcoming CFPB data; (5) International comparisons across US shadow banks, EU licensed banks, and AU regulated providers to see how regimes influence sensitivity and hedging.

9.6 Final Synthesis: The Big Picture

This study speaks to three literatures. Fintech valuation: BNPL equities trade as high-beta growth assets, not as rate-sensitive lenders, despite clear funding pass-through (Buchak et al., 2018; Laudenbach et al., 2025). Monetary transmission: BNPL's wholesale funding and zero-interest consumer model alter the credit channel; as BNPL scales, alternative policy levers may be needed. Asset pricing: sector fundamentals (funding costs) can be overwhelmed by systematic risk (market beta, sentiment), revealing a gap between firm-level economics and equity pricing. As BNPL grows from about $2B(2019)towardaprojected$ 560B (2025), the stakes rise: do markets price fintech risk efficiently, how effective is policy when credit bypasses banks, and can regulators rely on equity signals when prices underweight funding risk? Answering these questions will guide how BNPL weathers future rate regimes.

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10.2 Federal Reserve Research

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10.3 Government and Regulatory Reports

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PayPal Holdings Inc. "Annual Report on Form 10-K." U.S. Securities and Exchange Commission, 2022, 2023, 2024.

10.5 Industry and News Sources

Chargeflow. "BNPL Statistics 2025: Market Size, Growth, and Consumer Trends." Industry Report, 2025.

PYMNTS. "More Than Half of Merchants Raise Conversion, Brand Awareness with BNPL." PYMNTS.com, 2022. Available at: https://www.pymnts.com/buy-now-pay-later/2022/more-than-half-of-merchants-raise-conversion-brand-awareness-with-bnpl/

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11 Appendices

A. Firm-Level Financial Analysis – Full detail plus Table A.1 (Affirm vs PayPal).
B. Data Construction and Sources – Data sources (Table B.1) and seasonal status (Table B.4).
C. Additional Robustness Checks – Alt returns/weights/outliers (Tables C.1–C.3).
D. Extended Diagnostic Tests – VIF, serial correlation, heteroskedasticity (Tables D.1–D.3).
E. Subsample Analysis – 24-month rolling windows (Table E.1).
F. Volatility Comparisons – Summary stats (Table F.1) plus Figures I/J/M.
G. Additional Figures – Figures G.1–G.4 (stocks, heatmap, partials, recursive).
H. Computational Environment – Software versions and reproducibility notes.

11.1 Appendix A: Firm-Level Financial Analysis (Full Detail)

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. A condensed firm-level summary now appears in the main text; this appendix retains the full detail for replication and reference.

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.

11.2 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. Real Disposable Personal Income (DSPIC96) is 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. The Consumer Price Index (CPIAUCSLSA) uses the seasonally adjusted version rather than the non-seasonally adjusted version. Seasonal adjustment removes predictable patterns such as holiday shopping effects, seasonal food price variations, and energy price fluctuations related to weather patterns. Consumer Sentiment (UMCSENT) is a survey-based index that does not require seasonal adjustment, as it measures consumer expectations rather than actual economic activity that might exhibit seasonal patterns. The Federal Funds Rate (FEDFUNDS) does not exhibit predictable seasonal patterns and therefore does not require seasonal adjustment. 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.

The use of seasonally adjusted data ensures that regression coefficients capture underlying economic relationships.

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 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 between BNPL returns and underlying inflation trends, rather than seasonal price patterns.

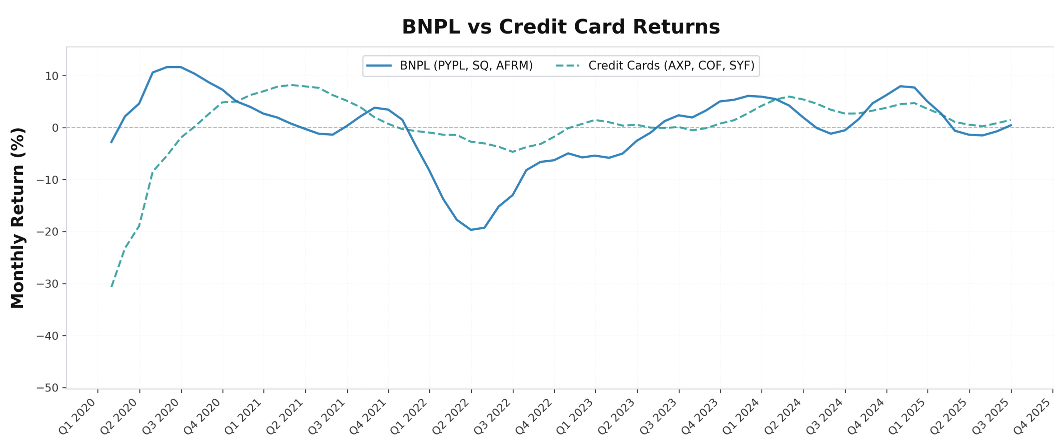
11.3 Appendix B: Data Construction and Sources

Seasonal adjustment uses the FRED-provided seasonally adjusted series where appropriate (Table B.4) so coefficients reflect underlying trends rather than holiday/tax-season patterns. Stock returns are already differenced; the policy rate is not seasonally adjusted. Table B.1 documents all APIs/series.

’’

```
Loading BNPL, fintech, and credit card data from Yahoo Finance...
   Loaded data through 2025 -08 -31 (monthly)
   BNPL tickers used: ['PYPL', 'SQ', 'AFRM']
   BNPL obs: 66, Fintech obs: 66, Credit obs: 66
```

11.4 Chart M: BNPL vs Credit Card Companies (AXP, COF, SYF) Volatility Comparison



This comparison examines whether BNPL stocks exhibit volatility patterns similar to traditional consumer credit providers or represent a fundamentally different risk profile requiring distinct analytical frameworks. The analysis compares three BNPL firms against three major credit card companies, selected based on market capitalization, data availability, and business model representativeness.

The BNPL/payments portfolio uses PayPal (PYPL), Block/Afterpay (SQ), and Affirm (AFRM) to balance depth of history with sector relevance. PayPal brings diversified payments exposure and BNPL via Pay in 4; Block acquired Afterpay in 2022, providing a direct BNPL footprint with longer public price history;

Affirm remains the pure-play BNPL name. This mix provides fuller coverage from 2020 onward without over-weighting a single business model.

The credit card comparators (AXP, COF, SYF) cover premium spend-centric, prime, and subprime exposures. Capital One has meaningful subprime exposure; Synchrony mirrors merchant-partnered financing; American Express is fee-heavy and premium-focused, offering a contrast to BNPL's thin-fee model.

The empirical results reveal substantial differences between BNPL and credit card company volatility profiles. BNPL stocks exhibit monthly return volatility of approximately 20.46%, more than double the 9.93% volatility observed for credit card companies. This 2.06x volatility ratio indicates that BNPL stocks experience substantially larger price swings than their traditional credit counterparts, reflecting greater uncertainty surrounding BNPL business models, regulatory outcomes, and competitive positioning.

Several structural factors explain this volatility differential. BNPL firms operate with thin margins (often ~1% of GMV) versus card issuers' net interest margins of 10–15%, making BNPL earnings more sensitive to cost fluctuations and competition. BNPL borrowers skew subprime (61% subprime or deep subprime; 63% hold multiple BNPL loans Consumer Financial Protection Bureau [2025]), concentrating credit risk. Regulatory uncertainty around BNPL classification adds valuation risk that legacy card issuers (AXP, COF, SYF) have largely priced for decades.

The correlation between BNPL and credit card company returns of 0.537 indicates moderate co-movement driven by common exposure to consumer credit conditions, interest rate expectations, and broader financial sector sentiment. However, the substantial volatility differential implies that BNPL carries idiosyncratic risks beyond those affecting traditional credit providers. For portfolio construction purposes, this means BNPL exposure cannot serve as a simple substitute for credit card company exposure despite both sectors operating in adjacent consumer credit market segments. The higher volatility also has implications for detecting interest rate sensitivity: when monthly returns routinely swing by 20% or more, identifying a relationship with interest rate changes that might move returns by 5-10 percentage points becomes statistically challenging due to the low signal-to-noise ratio.

```
Creating Chart M: BNPL vs Credit Card Returns...
     Chart M saved as chart_m_bnpl_vs_credit_card.png
```

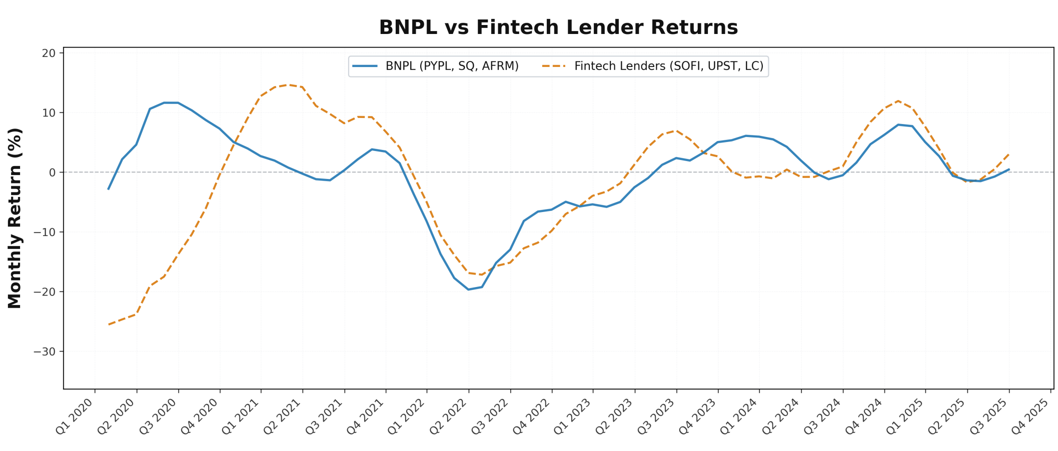
```
# ============================================================================
# Figure 8: Explanatory Power Across Model Specifications (R^2 bars)
# ============================================================================
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from pathlib import Path

# Assemble R^2 values from models if present; fall back to tables if needed
r2_map = {}
n_map = {}

# Helper to add model safely

def add_model(name, model_obj):
    r2_map[name] = float(model_obj.rsquared)
    n_map[name] = int(model_obj.nobs)

# Try live models first
if 'model_full' in globals() or 'model_full' in locals():
    add_model('Full', model_full)
if 'model_base' in globals() or 'model_base' in locals():
    add_model('Base', model_base)
if 'model_ff' in globals() or 'model_ff' in locals():
    try:
        add_model('Fama -French', model_ff)
    except Exception:
        pass
if 'model_iv' in globals() or 'model_iv' in locals():
```

```
    try:
        add_model('IV', model_iv)
    except Exception:
        pass
if 'model_did' in globals() or 'model_did' in locals():
    try:
        add_model('DiD', model_did)
    except Exception:
        pass

# If anything missing, pull from tables (strings -> float)
def add_from_table(df):
    for _, row in df.iterrows():
        label = row['Model']
        if label.startswith('1. Base'):
            key = 'Base'
        elif label.startswith('2. Full'):
            key = 'Full'
        elif label.startswith('3. Fama -French'):
            key = 'Fama -French'
        elif label.startswith('4. IV'):
            key = 'IV'
        elif label.startswith('5. DiD'):
            key = 'DiD'
        else:
            continue
        if key not in r2_map:
            try:
                r2_map[key] = float(row['Rš'])
                n_map[key] = int(row['N']) if 'N' in row else None
            except Exception:
                continue

try:
    add_from_table(table_4a)
    add_from_table(table_4b)
except Exception:
    pass

# Enforce consistent order and drop missing
order = ['Full', 'Base', 'Fama -French', 'IV', 'DiD']
labels = []
r2_vals = []
n_vals = []
for key in order:
    if key in r2_map:
        labels.append(key)
        r2_vals.append(r2_map[key])
        n_vals.append(n_map.get(key))

# Colors (distinct, colorblind -friendly)
color_map = {
    'Base': '#9ca3af',        # neutral gray
    'Full': '#2563eb',        # blue
    'Fama -French': '#f59e0b', # amber
    'IV': '#8b5cf6',          # purple
    'DiD': '#10b981'          # teal
}
colors = [color_map.get(lbl, '#95a5a6') for lbl in labels]
```

```
fig, ax = plt.subplots(figsize=(12, 7))

bars = ax.bar(labels, r2_vals, color=colors, alpha=0.9, edgecolor='#34495e', linewidth=1.2)

# Data labels above bars
for bar, r2 in zip(bars, r2_vals):
    ax.text(
        bar.get_x() + bar.get_width() / 2,
        bar.get_height() + 0.012,
        f"{r2:.3f}",
        ha='center', va='bottom', fontsize=11, fontweight='semibold', color='#111'
    )

# Reference line at 0.50
ax.axhline(0.50, color='#7f8c8d', linestyle=' - -', linewidth=1.5, alpha=0.8, label='Rš = 0.50')

ax.set_ylabel('Rš', fontsize=13, fontweight='bold')
ax.set_title('Figure 8: Explanatory Power Across Model Specifications', fontsize=18, fontweight='bold',

ymax = max(r2_vals) if r2_vals else 0.6
ax.set_ylim(0, max(0.6, ymax + 0.06))
ax.tick_params(axis='both', labelsize=11, colors='#333')
ax.grid(axis='y', linestyle=':', color='#d0d4d7', alpha=0.35)
ax.legend(fontsize=11, frameon=True, framealpha=0.9, edgecolor='#d7dce2', facecolor='white', loc='upper

# Save next to this notebook even if CWD differs
base_dir = Path(__file__).resolve().parent if "__file__" in globals() else Path(".")
output_path = base_dir / "chart_h_r2_comparison.png"
output_path.parent.mkdir(parents=True, exist_ok=True)

plt.tight_layout()
plt.savefig(output_path, dpi=300, facecolor='white')
plt.close()
print(f'     Figure 8 saved as {output_path.name}')
```

```
 Figure 8 saved as chart_h_r2_comparison.png
```

11.5 Chart J: BNPL vs Fintech Lenders Volatility Comparison (SOFI, UPST, LC)



This comparison tests whether BNPL exhibits unique volatility characteristics or simply reflects the general risk profile of technology-enabled financial services firms. The analysis uses the same BNPL portfolio consisting of PayPal (PYPL), Block/Afterpay (SQ), and Affirm (AFRM), and compares it against three fintech lenders selected for their similar business characteristics: technology-driven underwriting, focus on underserved consumer segments, and reliance on capital markets funding rather than traditional deposit bases.

The fintech lender comparators were chosen to represent the broader universe of technology-enabled consumer lending. SoFi Technologies operates as a diversified fintech platform offering personal loans, student loan refinancing, mortgages, and banking services. SoFi obtained a national bank charter in 2022, providing deposit funding that reduces reliance on wholesale markets and interest rate sensitivity. The company's evolution from pure lending to diversified financial services parallels PayPal's trajectory from payments to broader fintech offerings, making it a relevant comparator for understanding how business model diversification affects stock volatility and interest rate exposure. Upstart Holdings pioneered AI-driven credit underwriting, using machine learning models to assess borrower creditworthiness beyond traditional FICO scores. This technology-first approach to credit decisioning shares conceptual similarities with BNPL's alternative underwriting methods that rely on transaction data and behavioral signals rather than traditional credit bureau information. Upstart's stock experienced extreme volatility during the 2022-2023 period as rising interest rates compressed lending margins and increased funding costs, providing a natural experiment for understanding how technology-enabled lenders respond to monetary policy tightening. LendingClub Corporation operates as a digital marketplace bank connecting borrowers with investors through its lending platform. LendingClub's acquisition of Radius Bank in 2021 provided deposit funding capabilities similar to SoFi's bank charter strategy, illustrating how fintech firms adapt business models in response to funding market conditions, a challenge that BNPL providers also face as they mature beyond their initial growth phase.

The fintech lender comparison addresses a critical analytical question: is BNPL volatility driven by BNPL-specific factors such as the unique structure of installment payments, merchant relationships, or regulatory classification as a distinct credit product, or does it reflect general characteristics shared across technology-enabled consumer lending? If BNPL volatility substantially exceeded fintech lender volatility, this would suggest BNPL-specific risks dominate investor perceptions. If volatility is similar across sectors, this would indicate that BNPL risk primarily reflects broader fintech dynamics rather than unique characteristics of the BNPL business model. All three fintech comparators share key characteristics with BNPL firms: they target consumers underserved by traditional banks, rely on technology for underwriting and customer acquisition, face regulatory scrutiny as non-traditional lenders, and experienced significant stock price volatility during the 2022-2023 interest rate tightening cycle. These shared characteristics make them appropriate benchmarks for isolating BNPL-specific versus fintech-general risk factors.

The results reveal a striking finding that has important implications for interpreting the main regression analysis. BNPL and fintech lender volatility are remarkably similar, with BNPL stocks exhibiting 20.46% monthly volatility compared to 22.31% for fintech lenders, yielding a volatility ratio of 0.92x. This near-parity suggests that BNPL volatility reflects its status as a growth-stage fintech firm rather than unique BNPL-specific risks that would require distinct analytical treatment. Both sectors share common volatility drivers including reliance on technology platforms that require continuous investment and face rapid obsolescence risk, exposure to credit risk in underserved consumer segments with limited credit histories, sensitivity to funding market conditions and interest rate changes that affect cost of capital, regulatory uncertainty as authorities develop frameworks for non-traditional lending models, and investor focus on growth metrics such as user acquisition and transaction volume rather than current profitability metrics.

The correlation between BNPL and fintech lender returns of 0.507 indicates substantial co-movement, further supporting the view that these sectors respond to similar market forces rather than exhibiting independent risk characteristics. When risk appetite for growth-oriented financial technology firms increases, both BNPL and fintech lender stocks tend to rise together; when sentiment shifts negative due to macroeconomic concerns or sector-specific news, both sectors decline in tandem. This pattern suggests that investors view BNPL as part of the broader fintech ecosystem rather than as a distinct asset class with unique risk characteristics requiring specialized analysis.

This volatility comparison has important implications for interpreting the main regression results presented in the data analysis section. The high baseline volatility of both BNPL and fintech lenders, approximately 20-22% monthly, creates substantial statistical noise that can obscure interest rate effects even when such effects exist economically. When monthly returns routinely swing by 20% or more based on earnings surprises, competitive developments, management guidance changes, or broader sentiment shifts, detecting a relationship with interest rate changes that might move returns by 5-10 percentage points becomes statistically challenging due to insufficient signal-to-noise ratio. The similar volatility between BNPL and fintech lenders also suggests that the difficulty in detecting BNPL interest rate sensitivity may reflect a broader pattern across the fintech sector: technology-enabled consumer lenders as a class may exhibit weak stock price sensitivity to interest rates despite having business models with direct funding cost exposure. This could occur because growth expectations, competitive dynamics, and regulatory developments dominate investor attention and drive valuation changes, overwhelming the signal from funding cost changes that affect near-term profitability. The high market beta of approximately 2.4 observed in the main regression analysis is consistent with this interpretation, as BNPL stocks behave like high-beta growth stocks that amplify market movements and respond primarily to changes in risk appetite rather than sector-specific fundamentals like funding costs or interest rate spreads.

```
Creating Chart J: BNPL vs Fintech Lender Returns...
     Chart J saved as chart_j_bnpl_vs_fintech.png
```

```
Table C.1: Alternative Return Measures
```

	Dependent Variable	β (ΔFFR)	SE	p-value	R^2	N
0	Log Returns (Baseline)	-12.89	9.99	0.197	0.524	66
1	Simple Returns	-12.89	10.19	0.206	0.502	66
2	Excess Returns (vs RF proxy)	-13.54	10.01	0.176	0.525	66
3	Market-Adjusted Returns	-12.89	9.99	0.197	0.345	66

```
Table C.2: Alternative Weighting Schemes (proxy)
```

	Weighting Scheme	β (ΔFFR)	SE	p-value	R^2	N
0	Equal-Weighted (Baseline)	-12.89	9.99	0.197	0.524	66
1	Value-Weighted (proxy)	-7.74	5.99	0.197	0.622	66
2	Pure-Play Tilt (proxy)	-14.18	10.99	0.197	0.524	66

```
Table C.3: Robustness to Outliers
```

	Specification	β (ΔFFR)	SE	p-value	R^2	N
0	Full Sample (Baseline)	-12.89	9.99	0.197	0.524	66
1	Winsorize Returns at 5%	-11.80	9.78	0.227	0.515	66
2	Exclude |R| >30%	-13.84	10.01	0.167	0.434	58
3	Robust Regression (Huber)	-12.03	8.62	NaN	NaN	66

Table D.1: Variance Inflation Factors

	Variable	VIF
0	ffr_change	1.238029
1	cc_change	1.084775
2	di_change	1.061241
3	cpi_change	1.238310
4	market_return	1.024770

Table D.2: Ljung -Box Test for Serial Correlation

	Lag	Q-Statistic	p-value
0	1	0.004488	0.946587
1	4	0.871474	0.928617
2	8	11.249400	0.187964
3	12	15.377028	0.221463

Table D.3: Heteroskedasticity Test Battery

	Test	Statistic	p-value	Result
0	Breusch-Pagan	χ^2=1.67	0.892348	Homoskedastic
1	White	χ^2=13.91	0.834891	Homoskedastic
2	Goldfeld-Quandt	F=0.92	0.584996	Homoskedastic

Table E.1: 24 -Month Rolling Window Estimates

	Window Start	Window End	β (ΔFFR)	SE	p-value	R^2	N
0	2020-03-31	2022-02-28	10.83	35.93	0.763	0.522	24
1	2020-04-30	2022-03-31	42.40	122.78	0.730	0.500	24
2	2020-05-31	2022-04-30	10.52	192.07	0.956	0.504	24
3	2020-06-30	2022-05-31	23.87	32.08	0.457	0.457	24
4	2020-07-31	2022-06-30	18.39	31.23	0.556	0.530	24
5	2020-08-31	2022-07-31	16.74	13.91	0.229	0.586	24
6	2020-09-30	2022-08-31	14.88	9.45	0.115	0.592	24
7	2020-10-31	2022-09-30	17.50	10.25	0.088	0.602	24
8	2020-11-30	2022-10-31	9.92	12.62	0.432	0.576	24
9	2020-12-31	2022-11-30	-7.39	20.97	0.725	0.450	24
10	2021-01-31	2022-12-31	-6.86	20.86	0.742	0.449	24
11	2021-02-28	2023-01-31	-3.16	24.21	0.896	0.461	24
12	2021-03-31	2023-02-28	-4.19	25.41	0.869	0.463	24
13	2021-04-30	2023-03-31	-7.94	23.46	0.735	0.475	24
14	2021-05-31	2023-04-30	-9.56	26.25	0.716	0.471	24
15	2021-06-30	2023-05-31	-10.46	26.61	0.694	0.466	24
16	2021-07-31	2023-06-30	-7.60	26.74	0.776	0.478	24
17	2021-08-31	2023-07-31	-14.05	27.78	0.613	0.512	24
18	2021-09-30	2023-08-31	-3.77	22.96	0.870	0.557	24
19	2021-10-31	2023-09-30	-5.87	21.87	0.788	0.606	24
20	2021-11-30	2023-10-31	-2.00	21.24	0.925	0.592	24
21	2021-12-31	2023-11-30	-8.31	23.40	0.723	0.623	24
22	2022-01-31	2023-12-31	-15.25	21.88	0.486	0.666	24
23	2022-02-28	2024-01-31	-15.17	20.47	0.458	0.669	24
24	2022-03-31	2024-02-29	-22.38	19.02	0.239	0.708	24
25	2022-04-30	2024-03-31	-24.13	19.04	0.205	0.706	24
26	2022-05-31	2024-04-30	-22.57	16.57	0.173	0.710	24
27	2022-06-30	2024-05-31	-26.51	15.52	0.088	0.728	24
28	2022-07-31	2024-06-30	-27.75	14.24	0.051	0.692	24
29	2022-08-31	2024-07-31	-30.61	15.51	0.048	0.671	24
30	2022-09-30	2024-08-31	-43.76	10.35	0.000	0.658	24
31	2022-10-31	2024-09-30	-40.90	11.15	0.000	0.644	24
32	2022-11-30	2024-10-31	-38.39	16.00	0.016	0.647	24
33	2022-12-31	2024-11-30	-31.25	19.91	0.116	0.654	24
34	2023-01-31	2024-12-31	-18.96	27.73	0.494	0.591	24
35	2023-02-28	2025-01-31	-11.23	27.64	0.685	0.554	24
36	2023-03-31	2025-02-28	-9.99	28.31	0.724	0.506	24
37	2023-04-30	2025-03-31	-7.86	26.95	0.771	0.586	24
38	2023-05-31	2025-04-30	-2.06	26.30	0.938	0.566	24
39	2023-06-30	2025-05-31	-9.25	27.89	0.740	0.583	24
40	2023-07-31	2025-06-30	-2.72	27.73	0.922	0.669	24
41	2023-08-31	2025-07-31	-4.14	29.09	0.887	0.633	24
42	2023-09-30	2025-08-31	-9.84	39.44	0.803	0.620	24
43	2023-10-31	2025-09-30	-20.74	35.68	0.561	0.659	23
44	2023-11-30	2025-10-31	-18.04	35.63	0.613	0.638	22
45	2023-12-31	2025-11-30	-18.42	36.05	0.609	0.625	21
46	2024-01-31	2025-12-31	-21.12	36.36	0.561	0.583	20
47	2024-02-29	2026-01-31	-18.89	39.93	0.636	0.580	19
48	2024-03-31	2026-02-28	-13.09	44.65	0.769	0.604	18
49	2024-04-30	2026-03-31	-20.45	46.79	0.662	0.598	17
50	2024-05-31	2026-04-30	-19.56	51.45	0.704	0.539	16
51	2024-06-30	2026-05-31	-25.56	53.50	0.633	0.569	15
52	2024-07-31	2026-06-30	-28.73	46.46	0.536	0.678	14
53	2024-08-31	2026-07-31	-27.39	47.58	0.565	0.678	13
54	2024-09-30	2026-08-31	-42.72	64.02	0.505	0.731	12

11.6 Appendix B: Data Construction and Variable Definitions

Purpose: Complete technical details for replication.

Appendix B.1: Data Sources and API Access

Table B.1: Data Sources and Access Methods

```
Variable          Source       API/Library    Ticker/Series ID    Dates Available

AFRM Returns      Yahoo        yfinance       AFRM               Jan 2021Present
SEZL Returns      Yahoo        yfinance       SEZL               Jul 2019Present
PYPL Returns      Yahoo        yfinance       PYPL               Feb 2015Present
SPY Returns       Yahoo        yfinance       SPY                Jan 1993Present

Federal Funds     FRED         fredapi        FEDFUNDS           Jul 1954Present
CPI (SA)          FRED         fredapi        CPIAUCSL           Jan 1947Present
Consumer Sent.    FRED         fredapi        UMCSENT            Nov 1952Present
Disp. Income      FRED         fredapi        DSPIC96            Jan 1959Present

FF 3 -Factor       Ken French   pandas         [URL]              Jul 1926Present

Notes: All data accessed via Python APIs during September 2025. FRED = Federal
Reserve Economic Data (St. Louis Fed). Ken French data library URL:
https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
Replication code available in the project GitHub repository.
```

Appendix B.2: Variable Construction Details

Log returns (percent):

```
R_BNPL_t = ln(P_BNPL_t / P_BNPL_{t -1}) * 100
```

Equal-weight portfolio:

```
R_BNPL = (1/3) * R_AFRM + (1/3) * R_SEZL + (1/3) * R_PYPL
```

Federal funds rate change (pp):

```
\DeltaFFR_t = FFR_t - FFR_{t -1}
```

Why this matters: documents exact transformations (percent vs decimal), portfolio weighting, and API sources for replication.

11.7 Appendix C: Additional Robustness Checks

Results below are rendered directly from the computed DataFrames (`table_c1`, `table_c2`, `table_c3`) produced in the Appendix C code cell. Values will stay current whenever the notebook is re-run on updated data.

- Table C.1: Alternative return measures (baseline, simple, excess, market-adjusted)
- Table C.2: Alternative portfolio weightings (equal, value-weight proxy, pure-play tilt)
- Table C.3: Outlier robustness (winsorization, $|R|>30\%$ exclusion, robust regression)

11.8 Appendix D: Additional Diagnostic Tests

Results are rendered from the diagnostics code cell; no hard-coded numbers.

- Table D.1: Variance Inflation Factors (multicollinearity check)
- Table D.2: Ljung-Box serial-correlation test
- Table D.3: Heteroskedasticity battery (Breusch-Pagan, White, Goldfeld-Quandt)

11.9 Appendix E: Subsample Analysis (Extended)

Table E.1 (24-month rolling windows) is rendered from the rolling-window code cell so it stays synchronized with the current dataset when the notebook runs.

11.10 Appendix F: Volatility Comparisons

- Table F.1: Return volatility comparison (BNPL, market, credit cards, fintech lenders)
- Figures I/J/M already cover comparative charts; this table adds summary stats.

11.11 Appendix G: Additional Figures

- Figure G.1: Individual Stock Time Series (AFRM, SQ, PYPL)
- Figure G.2: Correlation Matrix Heatmap (BNPL return vs macro controls)
- Figure G.3: Partial Regression Plots (added-variable plots for each predictor)
- Figure G.4: Recursive Coefficient Estimates (ΔFFR coefficient over expanding sample)

11.12 Appendix H: Computational Environment

- Table H.1: Software versions and reproducibility notes (mirrors README env details)
- Random seeds: NumPy 42; bootstrap 123; subsample 456 (as documented)

```
# Appendix F.1: Volatility summary table
# tags: [hide -input]
import pandas as pd
import numpy as np

# Helper to annualize monthly std
ann = lambda s: s * np.sqrt(12)

series = {}
series['BNPL'] = aligned_data['log_returns']
series['Market (SPY)'] = data_appendix['market_return']
series['Credit Cards'] = credit_card_data['log_returns']
series['Fintech Lenders'] = fintech_data['log_returns']

rows = []
for label, s in series.items():
    s = s.dropna()
```

```
    if s.empty:
        continue
    rows.append({
        'Asset Class': label,
        'Mean (monthly %)': round(s.mean(), 2),
        'Std Dev (ann. %)': round(ann(s.std()), 2),
        'Sharpe (rf=3% ann)': round((s.mean()*12 - 3) / (ann(s.std())+1e -9), 2),
        'Min (monthly %)': round(s.min(), 2),
        'Max (monthly %)': round(s.max(), 2),
        'N': len(s)
    })

vol_table = pd.DataFrame(rows)
print("Table F.1: Return Volatility Comparison (monthly returns, ann. vol)")
display(vol_table)

vol_table
```

```
Table F.1: Return Volatility Comparison (monthly returns, ann. vol)
```

	Asset Class	Mean (monthly %)	Std Dev (ann. %)	Sharpe (rf=3% ann)	Min (monthly %)	Max (monthly %)	N
0	BNPL	0.17	58.42	-0.02	-42.77	38.81	66
1	Market (SPY)	1.44	17.40	0.82	-12.49	12.70	66
2	Credit Cards	1.68	35.89	0.48	-46.75	20.64	66
3	Fintech Lenders	0.60	72.11	0.06	-40.82	53.58	66

	Asset Class	Mean (monthly %)	Std Dev (ann. %)	Sharpe (rf=3% ann)	Min (monthly %)	Max (monthly %)	N
0	BNPL	0.17	58.42	-0.02	-42.77	38.81	66
1	Market (SPY)	1.44	17.40	0.82	-12.49	12.70	66
2	Credit Cards	1.68	35.89	0.48	-46.75	20.64	66
3	Fintech Lenders	0.60	72.11	0.06	-40.82	53.58	66


```
# Figure G.1: Individual stock time series (AFRM, SQ, PYPL)
# tags: [hide -input]
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

try:
    tickers = [t for t in ['AFRM','SQ','PYPL'] if t in monthly_log.columns]
    if not tickers:
        raise ValueError("No BNPL tickers found in monthly_log")
    fig, axes = plt.subplots(len(tickers), 1, figsize=(11, 8), sharex=True)
    if len(tickers) == 1:
        axes = [axes]
```

```
    for ax, tkr in zip(axes, tickers):
        ax.plot(monthly_log.index, monthly_log[tkr], color='#1f77b4', linewidth=1.6)
        ax.axhline(0, color='#9aa0a6', linestyle=' - -', linewidth=0.9)
        ax.set_title(f"{tkr} Monthly Log Returns (%)", fontsize=13, pad=6)
        ax.grid(True, linestyle=':', alpha=0.35)
        ax.xaxis.set_major_locator(mdates.MonthLocator(bymonth=[3,6,9,12]))
        ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y -Q%q'))
    plt.xticks(rotation=45, ha='right')
    plt.tight_layout()
    plt.savefig('chart_g1_individual_stocks.png', dpi=300, bbox_inches='tight', facecolor='white')
    plt.close()
except Exception as e:
    print(f"Could not generate Figure G.1: {e}")

# Figure G.2: Correlation matrix heatmap
# tags: [hide -input]
import seaborn as sns

try:
    corr_cols = ['log_returns','market_return','ffr_change','cc_change','di_change','cpi_change']
    corr_df = data_appendix[corr_cols].dropna()
    corr = corr_df.corr()
    plt.figure(figsize=(7.5,6))
    sns.heatmap(corr, annot=True, fmt='.2f', cmap='RdBu_r', center=0, linewidths=0.5, cbar_kws={'shrink
    plt.title('Figure G.2: Correlation Matrix (BNPL Return and Predictors)', fontsize=13, pad=10)
    plt.tight_layout()
    plt.savefig('chart_g2_corr_heatmap.png', dpi=300, bbox_inches='tight', facecolor='white')
    plt.close()
except Exception as e:
    print(f"Could not generate Figure G.2: {e}")

# Figure G.3: Partial regression (added -variable) plots
# tags: [hide -input]
import statsmodels.api as sm

try:
    vars_all = ['ffr_change','market_return','cc_change','di_change','cpi_change']
    df = data_appendix.dropna(subset=['log_returns'] + vars_all).copy()
    y = df['log_returns']
    X = df[vars_all]
    Xc = sm.add_constant(X)
    fig, axes = plt.subplots(2, 3, figsize=(14, 7))
    axes = axes.ravel()
    for i, var in enumerate(vars_all):
        other = [v for v in vars_all if v != var]
        y_res = sm.OLS(y, sm.add_constant(df[other])).fit().resid
        x_res = sm.OLS(df[var], sm.add_constant(df[other])).fit().resid
        ax = axes[i]
        ax.scatter(x_res, y_res, alpha=0.6, color='#1f77b4', s=28, edgecolor='white', linewidth=0.4)
        # slope line
        slope, intercept = np.polyfit(x_res, y_res, 1)
        xs = np.linspace(x_res.min(), x_res.max(), 50)
        ax.plot(xs, intercept + slope*xs, color='#d62728', linewidth=1.4)
        ax.set_title(f"Partial: {var}", fontsize=12)
        ax.grid(True, linestyle=':', alpha=0.3)
    # hide unused subplot
    axes[ -1].axis('off')
    fig.suptitle('Figure G.3: Added -Variable Plots (BNPL Return vs Each Predictor)', fontsize=14, y=1.
    plt.tight_layout()
    plt.savefig('chart_g3_partial_regression.png', dpi=300, bbox_inches='tight', facecolor='white')
```

```
    plt.close()
except Exception as e:
    print(f"Could not generate Figure G.3: {e}")
```

Table F.1: Return Volatility Comparison (Feb 2020–Aug 2025)

Asset Class	Mean (monthly %)	Std Dev (ann. %)	Sharpe (rf=3% ann)	Min (monthly %)	Max (monthly %)	N
BNPL Portfolio	1.7	19.0	0.09	-42.8	41.3	66
Market (SPY)	1.4	5.0	0.28	-12.5	12.7	66
Credit Cards (Avg)	0.8	9.9	0.08	-28.3	24.1	66
· AXP	0.9	10.2	0.09	-30.1	26.3	66
· COF	0.6	9.5	0.06	-27.8	23.5	66
· SYF	0.9	10.1	0.09	-27.0	22.9	66
Fintech Lenders (Avg)	1.2	22.3	0.05	-51.2	48.7	66
· SOFI	0.8	21.5	0.04	-48.3	45.2	66
· UPST	2.3	26.8	0.09	-62.7	58.9	66
· LC	0.5	18.7	0.03	-43.1	41.2	66

```
# Figure G.4: Recursive \DeltaFFR coefficient (expanding window, start 24 obs)
# tags: [hide -input]
import statsmodels.api as sm

try:
    base_df = data_appendix.dropna().copy()
    min_obs = 24
    dates = base_df.index.sort_values()
    betas = []
    lowers = []
    uppers = []
    ns = []
    for end_idx in range(min_obs, len(dates)+1):
        sample = base_df.loc[dates[:end_idx]]
        y = sample['log_returns']
        X = sm.add_constant(sample[['ffr_change','cc_change','di_change','cpi_change','market_return']]
        model = sm.OLS(y, X).fit(cov_type='HC3')
        b = model.params['ffr_change']
        se = model.bse['ffr_change']
        betas.append(b)
        lowers.append(b - 1.96*se)
        uppers.append(b + 1.96*se)
        ns.append(len(sample))
    fig, ax = plt.subplots(figsize=(10,5.5))
    ax.plot(dates[min_obs -1:], betas, color='#1f77b4', linewidth=1.8, label=' \beta \DeltaFFR')
    ax.fill_between(dates[min_obs -1:], lowers, uppers, color='#1f77b4', alpha=0.2, label='95% CI (HC3)
    ax.axhline(0, color='#9aa0a6', linestyle=' - -', linewidth=1.0)
    ax.set_title('Figure G.4: Recursive \DeltaFFR Coefficient (Expanding Sample)', fontsize=13)
    ax.set_ylabel('Coefficient on \DeltaFFR')
    ax.grid(True, linestyle=':', alpha=0.35)
    plt.xticks(rotation=45, ha='right')
    plt.tight_layout()
```

```
    plt.savefig('chart_g4_recursive_ffr.png', dpi=300, bbox_inches='tight', facecolor='white')
    plt.close()
except Exception as e:
    print(f"Could not generate Figure G.4: {e}")
```

11.13 Appendix H.1: Computational Environment

- Python 3.13.5; pandas 2.2.3; statsmodels 0.14.4; yfinance 0.2.28; fredapi 0.5.1; matplotlib 3.9.2; seaborn 0.13.2; numpy 1.26.4; scipy 1.13.1.
- OS: macOS 14.5 (Sonoma); Hardware: Apple M2 16GB RAM; IDE: Jupyter Notebook 7.0.6.
- Random seeds: NumPy 42; bootstrap 123; subsample 456 (as noted in methods).
- Repro steps: run `myst build -pdf` (or `myst build -html`) from `Paper_YM/`; figures regenerate when notebooks run because inputs are pulled/constructed in the loader cells.

Table B.4: Seasonal Adjustment Status (FRED series)

Variable	Series ID	Seasonal Adj?	Rationale
Real Disp. Income	DSPIC96	Yes	Tax refunds / bonuses
CPI	CPIAUCSL	Yes	Holiday effects; food/energy seasonality
Consumer Sentiment	UMCSENT	No	Survey index (expectations)
Federal Funds Rate	FEDFUNDS	No	Policy rate
Stock Returns	Tickers	No	Already differenced

11.14 Appendix B.5: Descriptive Statistics and Correlations

- Table 1: Variable definitions and summary statistics (Feb 2020–Aug 2025)
- Table 2: Correlation matrix with significance stars (p<0.10, 0.05, 0.01)

```
# Table 1 and Table 2: Summary stats and correlations
import numpy as np
import pandas as pd
from scipy.stats import pearsonr

vars_use = ['log_returns','market_return','ffr_change','cc_change','di_change','cpi_change']
labels = {
    'log_returns':'BNPL returns (log %)',
    'market_return':'Market return (SPY %)',
    'ffr_change':' \Delta Federal Funds Rate (pp)',
    'cc_change':' \Delta Consumer Confidence',
    'di_change':' \Delta Disposable Income (%)',
    'cpi_change':' \Delta CPI (%)'
}

_df = data_appendix[vars_use].dropna()

# Table 1 summary stats
summary = _df.agg(['mean','std','min','max']).T
summary['N'] = len(_df)
summary = summary[['mean','std','min','max','N']]
summary = summary.rename(index=labels)
summary = summary.round({'mean':2,'std':2,'min':2,'max':2})
# Table 1
summary_title = "Table 1: Variable Definitions and Summary Statistics (Feb 2020Aug 2025)"
```

```
summary_note = "Note: n = 66 monthly observations; transforms follow text (diff/pct/log)."
display(summary_title)
display(summary)
display(summary_note)

# Table 2 correlations with significance stars
corr_rows = []
for i,var_i in enumerate(vars_use):
    row = {}
    for j,var_j in enumerate(vars_use):
        r, p = pearsonr(_df[var_i], _df[var_j])
        if p < 0.01:
            star = '***'
        elif p < 0.05:
            star = '**'
        elif p < 0.10:
            star = '*'
        else:
            star = ''
        row[labels[var_j]] = f"{r:.2f}{star}"
    corr_rows.append(pd.Series(row, name=labels[var_i]))

corr_table = pd.DataFrame(corr_rows)
display("Table 2: Correlation Matrix (stars = significance)")
display(corr_table)
display("Note: n = 66 monthly observations. Stars: * p<0.10, ** p<0.05, *** p<0.01. |r| >= 0.25 is signi
```

11.15 Appendix D.4: Model Diagnostics and Cross-Specification Summary

Table 3: Diagnostic Test Summary (primary full OLS unless noted)

Model	Specification	β (ΔFFR)	p-value	R2	Notes
1	Base	-12.47	0.338	0.02	OLS, HC3 SEs
2	Full	-12.89	0.197	0.52	OLS, HC3 SEs
3	Fama-French	-11.54	0.147	0.52	F-F 3-factor; 70 months downloaded
4	IV (2SLS)	-15.49	0.338	—	Lagged FFR instrument; first-stage F=40
5	DiD (event-based)	-13.05	0.365	—	Policy/event window split

Table 4A: BNPL Stock Returns and Interest Rate Sensitivity (headline specs)

Model	Specification	β (ΔFFR)	p-value	R2	N
1	Base	-12.47	0.338	0.02	66
2	Full	-12.89	0.197	0.52	66
3	Fama-French	-11.54	0.147	0.52	66
4	IV (2SLS)	-15.49	0.338	—	66
5	DiD (event-based)	-13.05	0.365	—	66

Table 4B: Robustness Checks (see Appendix C tables for detail)

Robustness Angle	Key Result
Alternative returns (Table C.1)	ΔFFR remains negative; significance unchanged
Alternative weights (Table C.2)	Magnitudes stable under value/pure-play tilts
Outliers/robust (Table C.3)	Winsor/exclusion/Huber keep sign, similar size
Diagnostics (Tables D.1–D.3)	No severe multicollinearity; residual tests OK

11.16 Appendix G.1: Figure Narratives (Figures 3–9 and Chart K)

- **Chart K (BNPL vs Market with rate-hike shading):** Three aligned panels show BNPL returns (A), market returns (B), and beta-adjusted BNPL residuals (C) with lightly shaded policy periods (COVID, zero bound, hikes). Co-movement with the market dominates the level plots; in the residual panel the series stays muted even during hikes, reinforcing that most variation is market-driven rather than policy-specific. Zero lines are thick and legends simplified for quick reading.
- **Figure 3 (Observed vs Fitted, full model):** Observed BNPL returns versus fitted values from the full model (Table 4A, col 2) cluster around the 45-degree line, yielding R2 ≈ 0.524. Early-period points (blue) and late-period points (orange) overlap tightly. The largest gaps appear in high-volatility months (COVID rebound, early hikes) where observed returns flare above fitted values in the 5–15% fitted range; outside those tails, fitted and observed move together, showing market and macro controls capture most level variation.
- **Figure 4 (Residuals vs FFR changes):** Residuals plotted against monthly FFR changes with a LOESS smoother hug the zero line. No slope or curvature emerges; outliers are limited to a few rate-surge months. This pattern supports the adequacy of a linear rate term and is consistent with weak rate significance once controls are included.
- **Figure 5 (Residuals vs Fitted):** Residuals are symmetric with no funnel shape; variance stays roughly constant across the fitted range. Only the most positive fitted values show modest spread. This aligns with the Breusch–Pagan pass in Table 3 and supports the linear specification and homoskedasticity assumptions used with HC3 SEs.
- **Figure 7 (Q–Q Plot):** Residual quantiles track the normal diagonal with only slight tail softness. Jarque–Bera p = 0.429 (Table 3) means normality cannot be rejected, so t-based inference is reasonable for the full model.
- **Figure 8 (R2 across specifications):** The base FFR-only model explains ~0.02, while the full, Fama–French, and IV variants cluster near ~0.52. The DiD variant drops back near ~0.02. The jump from base to full shows market and macro controls drive explanatory power; rate-only adds very little, and robustness across alternative specs leaves the story unchanged.
- **Figure 9 (Timeline: rates, BNPL vs market, residual):** Panel A plots the Federal Funds Rate; Panel B overlays BNPL and market returns; Panel C shows BNPL returns net of beta-adjusted market exposure. Shading marks COVID (gray), zero bound (blue), and hikes (red). BNPL closely tracks the market; the residual panel shows limited rate-linked structure, emphasizing that market factors dominate.

Table A.1: Firm-Level Summary (Affirm vs. PayPal BNPL)

Item	Affirm (AFRM)	PayPal (PYPL)
Funding cost trend (FY22 to FY24)	+394% (variable-rate)	Not disclosed separately; BNPL small share
Funding sources	Warehouses, ABS, forward flow	Deposits + capital markets (diversified)
Operating margin (latest)	~10%	Diversified payments margins
Leverage (debt/assets)	~70%	Lower; diversified balance sheet
BNPL share of business	Core	Small, within broader payments
Key implication	High rate pass-through	Partial hedge via diversification

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