Buy Now, Pay Later Stock Returns and Interest Rate Sensitivity

Yisheng (Bruce) Mao

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Abstract

This paper examines whether Buy Now, Pay Later (BNPL) stocks exhibit interest rate sensitivity comparable to traditional financial institutions. Despite firm-level evidence that BNPL funding costs rose 394% as rates increased from near-zero to 5.25%, I find no statistically significant rate sensitivity in monthly stock returns for either BNPL firms (β = -12.89, p = 0.197) or credit card issuers (β = 2.51, p = 0.777) using data from February 2020 to August 2025. BNPL stocks behave as high-beta growth assets (market β = 2.38), with market returns alone explaining 42% of return variation (from bivariate regression: $r^2 = 0.648^2$) versus only 2.4% for interest rates. Limited statistical power (15-20%) prevents definitive conclusions, but the results suggest that stock return sensitivity may differ substantially from firm-level funding cost sensitivity, particularly when firms can pass costs through to merchants and consumers. These findings highlight challenges in detecting monetary policy transmission through equity prices of non-bank financial intermediaries.

1 Introduction and Research Question

This paper quantifies the interest rate sensitivity of Buy Now, Pay Later (BNPL) stock returns and compares it to benchmarks from traditional financial institutions. Using monthly return data from February 2020 to August 2025 for three publicly traded BNPL providers, I estimate rate sensitivity coefficients and compare them to credit card issuers using identical specifications. I find that BNPL stocks exhibit economically large but statistically insignificant (imprecisely estimated) rate sensitivity (β = -12.89, SE = 9.99, p = 0.197), with high market beta (approximately 2.4) dominating return variation. The benchmark comparison reveals that credit card issuers also exhibit statistically weak rate sensitivity in monthly data, suggesting that detecting rate sensitivity in stock returns may be challenging even for rate-sensitive sectors.

1.1 Research Question and Theoretical Framework

The relationship between interest rates and BNPL stock returns operates through multiple channels with potentially offsetting effects. A simple valuation framework clarifies these mechanisms:

$$Stock\ Price = \sum_t \frac{E[Cash\ Flow_t]}{(1 + r + risk\ premium)^t} \tag{1}$$

An interest rate increase affects stock prices through two primary channels. First, the **cash flow channel** operates through funding costs: higher rates increase BNPL firms' funding costs (warehouse facilities, securitization), reducing expected cash flows. However, this effect may be offset if firms pass costs to merchants and consumers (Laudenbach et al. 2025 document 80-100% pass-through), or if higher credit card rates increase BNPL demand through competitive substitution. Second, the **discount rate channel** operates through valuation: higher risk-free rates increase the discount rate, reducing the present value of future cash flows. For growth-stage firms with long-duration cash flows, this channel can be substantial.

The net effect captured by the regression coefficient combines these offsetting channels. The direct funding cost channel predicts negative sensitivity, while competitive substitution predicts positive sensitivity. The discount rate channel predicts negative sensitivity, particularly for growth firms. Without a structural model that quantifies each channel, the regression captures the net effect, which may be small if channels offset.

1.2 Distinguishing Firm-Level and Stock-Level Sensitivity

A critical distinction separates firm-level funding cost sensitivity from stock return sensitivity. Firm-level evidence shows Affirm's funding costs increased 394% from FY2022 to FY2024, but this increase reflects both volume growth (more loans) and rate effects (higher rates on the same volume). Stock return sensitivity depends on whether investors anticipated these costs, whether firms can pass costs through, and whether growth expectations dominate valuation. A firm can have high funding cost sensitivity but low stock return sensitivity if investors anticipated rate increases and priced them in before they materialized, if firms pass costs to merchants and consumers, or if growth expectations dominate current profitability in valuation.

1.3 Research Hypotheses

I test three hypotheses. First, BNPL stock returns exhibit negative sensitivity to interest rate increases (H1). This hypothesis posits that β <0 for the interest rate coefficient, reflecting net negative effects of funding costs and discount rates outweighing any positive competitive substitution effects. Second, BNPL rate sensitivity is comparable in magnitude to traditional financial stocks (H2). This hypothesis posits that |β_BNPL - β_Financials| is statistically indistinguishable from zero when estimated using identical specifications over the same time period. Third, BNPL rate sensitivity is statistically weak in monthly return data, with high market beta dominating return variation (H3). This hypothesis posits that β_BNPL is statistically insignificant (p >0.15) while market beta >2.0 and R^2_market »R^2_rates, consistent with growth-oriented asset pricing.

1.4 Motivation and Context

In fiscal year 2024, Affirm Holdings reported funding costs of $344.3 million (Affirm 10-K, 2024), up 88$

The relationship between firm-level funding costs and stock returns is theoretically ambiguous. For growth-stage firms with negative operating margins, current funding costs may be economically irrelevant if investors believe the firm will achieve scale, diversify funding sources, or pass costs through. 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 (the Fed's tightening cycle was heavily telegraphed starting in late 2021), then realized monthly rate changes may have minimal impact because they were already priced in.

1.5 Empirical Approach

This investigation quantifies BNPL stock return sensitivity to interest rate changes and compares it to benchmarks from credit card issuers (American Express, Capital One, Synchrony Financial) using identical regression specifications. I estimate rate sensitivity coefficients for both BNPL and credit card issuers, allowing direct comparison of magnitudes and statistical precision. This benchmark comparison is essential because without establishing what "rate-sensitive financial institution" behavior looks like quantitatively, claims about BNPL behaving "differently" are untestable. Using 66 monthly return observations spanning February 2020 to August 2025, I estimate multiple specifications including base OLS, full OLS with controls, Fama-French three-factor models, instrumental variables, and difference-in-differences approaches to assess robustness.

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

The Buy Now, Pay Later sector has grown rapidly, yet empirical research on how BNPL firms respond to monetary policy changes remains limited. While extensive literature examines BNPL adoption, consumer behavior, and market growth, few studies directly analyze how interest rate changes affect BNPL firm performance through stock returns. This gap motivates the present analysis, which quantifies BNPL firms' interest rate sensitivity using stock return data while controlling for confounding factors. This review synthesizes three interconnected literatures: (1) interest rate sensitivity of financial institutions, which provides theoretical benchmarks and empirical patterns; (2) fintech valuation and funding structures, which reveal how technology-enabled lenders differ from traditional banks; and (3) BNPL market dynamics and consumer behavior, which illuminate demand-side factors that affect firm performance.

2.1 Interest Rate Sensitivity of Financial Institutions: Theoretical Benchmarks

Bank stock return sensitivity to interest rate changes provides a natural benchmark for evaluating BNPL rate sensitivity. Flannery and James (1984) establish the foundational framework, documenting that bank stock returns exhibit negative sensitivity to interest rate increases, with coefficients ranging from approximately -5 to -10 depending on bank characteristics **?**. Their analysis decomposes rate sensitivity into maturity mismatch effects and funding cost pass-through, finding that banks with greater maturity mismatches exhibit stronger negative sensitivity. This framework proves particularly relevant for BNPL firms, which face similar funding cost pressures but operate with different structural advantages and constraints.

English, Van den Heuvel, and Zakrajek (2018) extend this analysis using modern data and econometric methods, finding that U.S. bank stock returns exhibit economically and statistically significant negative sensitivity, with estimated coefficients of approximately $\beta \approx -6$ to -8 for large banks **?**. Critically, they document that rate sensitivity varies systematically with funding structures: banks that heavily rely on core deposits exhibit more pronounced negative sensitivity, while banks with substantial maturity mismatches experience less severe impacts. This finding informs expectations for BNPL firms, which rely almost exclusively on wholesale funding rather than deposits, suggesting potentially different sensitivity patterns than traditional banks with stable deposit bases.

Gandhi and Lustig (2015) examine asset pricing in bank stocks, finding that bank size influences exposure to market beta and interest rate sensitivity, with larger banks more sensitive to monetary policy shocks primarily transmitted through the market risk factor **?**. This dual nature—market beta exposure combined with rate sensitivity—creates a natural comparison point for BNPL stocks. If BNPL firms are priced similarly to banks, they should exhibit both market beta exposure and rate sensitivity. However, as subsequent sections reveal, BNPL firms may differ from banks in ways that affect this relationship.

Bernanke and Kuttner (2005) examine what explains stock market reactions to Federal Reserve policy, documenting that stock prices respond to monetary policy surprises primarily through the discount rate channel (affecting expected excess returns), with cash flow effects playing a smaller role **?**. Their framework for understanding how monetary policy affects equity valuations provides theoretical context for analyzing BNPL stock return sensitivity. The discount rate channel operates through valuation effects on expected returns, particularly relevant for growth-stage firms with long-duration cash flows, while cash flow channels may operate through various mechanisms including funding costs and profitability.

The theoretical prediction from this literature is clear: financial institutions with high reliance on wholesale funding, thin profit margins, and direct pass-through of funding costs should exhibit negative rate sensitivity with coefficients in the range of $\beta \approx -5$ to -10. Banks achieve this sensitivity through deposit-taking and lending activities, where rate increases raise funding costs faster than lending rates due to deposit rate stickiness. BNPL firms face similar funding cost pressures but lack the deposit funding advantage, suggesting potentially stronger negative sensitivity if funding costs fully pass through to profitability.

2.2 Fintech Valuation and Funding Structures: Regulatory Arbitrage and Operational Flexibility

The fintech literature reveals mechanisms through which technology-enabled lenders may differ from traditional banks in their response to interest rate changes. Buchak et al. (2018) provide crucial theoretical context, showing that fintech lenders exploit regulatory arbitrage to expand market share, with regulatory factors accounting for approximately 60% of shadow bank growth **?**. Fintech lenders charge a premium of 14-16 basis points, suggesting they offer convenience rather than cost savings. If BNPL firms can maintain market share through regulatory advantages and convenience features during rate hikes, funding costs may not fully affect profitability if firms can pass costs through or sustain temporary losses while maintaining competitive positioning. This mechanism may predict weaker rate sensitivity ($\beta_{BNPL} \approx 0$) than traditional banks if regulatory advantages allow operational flexibility, creating a competing theoretical prediction that contrasts with the bank-based benchmark.

Acharya et al. (2013) examine securitization structures and funding mechanisms, documenting how firms with arms-length funding (securitization, asset-backed securities) differ from bank-funded operations **?**. BNPL firms rely heavily on securitization and warehouse facilities, which may create different rate sensitivity patterns than bank-funded credit card operations. However, if securitization structures lock in fixed rates for extended periods, short-term rate changes may not immediately affect funding costs, creating a lagged sensitivity pattern. This tension between immediate pass-through (through variable-rate facilities) and delayed effects (through fixed-rate securitization) adds complexity to theoretical predictions.

Berg et al. (2020) examine the rise of fintechs and credit scoring using digital footprints, documenting how fintech lenders operate with different cost structures than traditional banks **?**. Their analysis reveals that fintech lenders use alternative data and pricing mechanisms that differ from traditional banks, which has implications for understanding how economic conditions affect BNPL demand and default risk. The concentration of BNPL usage among lower-creditworthiness consumers, combined with thin profit margins, suggests vulnerability to economic shocks that may amplify rate sensitivity through credit risk channels.

Fuster et al. (2019) examine the role of technology in mortgage lending, documenting how fintech lenders use technology to assess credit risk and serve different borrower segments **?**. Their analysis of fintech lending models provides insights into how technology-enabled lenders respond to economic conditions, which is relevant for understanding BNPL firm behavior. Technology-enabled credit assessment may allow BNPL firms to adjust pricing and risk management more quickly than traditional banks, potentially moderating rate sensitivity through operational flexibility.

2.3 Funding Structure Comparison: BNPL vs. Banks vs. Credit Cards

Theoretical predictions about rate sensitivity depend critically on funding structures. The following comparison examines funding models across BNPL providers, traditional banks, and credit card issuers, highlighting key differences that inform empirical expectations.

Table 1: Funding Structure Comparison: BNPL vs. Banks vs. Credit Cards

Characteristic	BNPL Providers	Traditional Banks	Credit Card Issuers
Primary Funding Sources	Warehouse credit facilities (variable-rate), securitization (mixed), commercial paper	Retail deposits (sticky rates), wholesale funding (variable-rate), interbank markets	Securitization (mixed), commercial paper, deposits (for bank-affiliated issuers)
Funding Cost Pass-Through	Immediate (variable-rate facilities tied to SOFR/LIBOR)	Partial (deposit rates adjust slowly; wholesale rates adjust immediately)	Immediate to partial (depends on securitization structure)
Profit Margins	Thin (approximately 1% net margins)	Moderate (10-15% net margins for large banks)	Moderate to high (15-25% net margins)
Rate Sensitivity Mechanism	Direct: funding costs rise immediately with benchmark rates	Indirect: deposit rate stickiness creates net interest margin compression	Direct to indirect: depends on funding mix and securitization terms
Expected β (Rate Coefficient)	-10 to -15 (if full pass-through) or -5 to -10 (if partial pass-through)	-5 to -10 (empirically documented)	-5 to -8 (similar to banks)
Market Beta	High (>2.0 expected due to growth orientation)	Moderate (0.8 to 1.2 typically)	Moderate (0.9 to 1.3 typically)
Regulatory Capital Requirements	Lower (non-bank lenders)	Higher (Basel III requirements)	Moderate (varies by issuer type)

This comparison reveals critical differences that generate competing theoretical predictions. BNPL providers face immediate funding cost pass-through through variable-rate warehouse facilities, suggesting potentially stronger negative rate sensitivity than banks if costs fully transmit to profitability. However, BNPL firms' thin profit margins (approximately 1%) limit their capacity to absorb funding cost shocks, creating pressure to pass costs through to merchants and consumers. If pass-through is complete, stock returns should be insensitive to funding costs. If pass-through is incomplete due to competitive pressures, stock returns should exhibit negative sensitivity.

Banks, by contrast, benefit from deposit rate stickiness, which creates a natural hedge: deposit rates adjust slowly while lending rates adjust more quickly, partially insulating net interest margins from rate changes. Credit card issuers occupy an intermediate position, with funding structures that vary by issuer type. This structural comparison sets up the empirical question: do BNPL firms exhibit stronger negative sensitivity than banks (due to immediate pass-through and lack of deposit advantages), or do they exhibit weak sensitivity (due to complete cost pass-through or regulatory arbitrage)?

2.4 Competing Theoretical Predictions

The funding structure comparison, combined with insights from fintech and banking literatures, generates four competing theoretical predictions. First, if BNPL firms operate like banks with immediate funding cost pass-through but without deposit advantages, they should exhibit stronger negative rate sensitivity than banks, with $\beta_{BNPL} < \beta_{Banks}$ (more negative), potentially in the range of $\beta_{BNPL} \approx -10$ to -15. Second, if BNPL firms can pass all funding costs to merchants and consumers through pricing adjustments, stock returns should be insensitive to funding costs ($\beta_{BNPL} \approx 0$). Third, if regulatory arbitrage allows BNPL firms to maintain below-market pricing during rate hikes, funding costs may not affect profitability, predicting weak or zero rate sensitivity ($\beta_{BNPL} \approx 0$) even if funding costs rise. Fourth, if securitization structures lock in fixed rates for extended periods, short-term rate changes may not immediately affect funding costs, creating lagged or weak sensitivity.

The empirical question is which mechanism dominates: competitive pressures and merchant bargaining power may prevent complete pass-through, while regulatory advantages may allow firms to sustain losses on funding costs. The empirical analysis tests these competing predictions by estimating rate sensitivity coefficients and comparing them to bank benchmarks.

2.5 Consumer Behavior and BNPL Demand: Demand-Side Factors

Research on consumer spending patterns and credit behavior provides foundational context for understanding BNPL market dynamics and how demand-side factors may moderate or amplify rate sensitivity. Gathergood et al. (2019) examine how individuals repay debt, finding that consumers use balance-matching heuristics that affect credit utilization patterns **?**. This research on debt repayment behavior is relevant for understanding BNPL usage, as BNPL transactions represent a form of credit that consumers must manage alongside other debt obligations. The spending response to BNPL access motivates the inclusion of consumer confidence as a control variable, as BNPL transaction volumes and firm revenues depend on consumer willingness to spend.

Powell et al. (2023) examine the relationship between responsible financial behaviors and financial wellbeing in the context of BNPL, documenting patterns of usage and repayment behavior **?**. Cervellati et al. (2025) analyze BNPL consumer credit behavior and its impacts on financing decisions, finding that BNPL services significantly affect consumers' financing decisions and highlighting the need for further exploration into their long-term financial implications **?**. These findings suggest that consumer financial conditions and attitudes toward BNPL may affect demand patterns, further justifying including consumer confidence measures in the regression framework. These demand-side factors create an additional channel through which interest rates may affect BNPL firm performance: higher rates reduce consumer spending power and confidence, potentially reducing BNPL transaction volumes independently of funding cost effects.

The literature on BNPL's effects on consumer financial health reveals important patterns relevant to understanding firm-level risk. de Haan, Kim, Lourie, and Zhu (2024) show that new BNPL users experience rapid increases in bank overdraft charges and credit card interest and fees relative to non-users, consistent with BNPL facilitating overborrowing **?**. These findings indicate that BNPL users may be financially fragile, which has implications for firm-level credit risk: financially fragile customers may experience higher default rates during monetary tightening cycles, potentially affecting BNPL firm profitability and stock returns through credit loss channels.

Gerrans, Baur, and Lavagna-Slater (2022) examine fintech and responsibility in BNPL arrangements, analyzing consumer behavior and over-indebtedness concerns, particularly among younger consumers and those in deprived areas **?**. 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. This vulnerability creates a second channel for rate sensitivity: even if funding costs are fully passed through, higher rates may increase default rates among financially fragile borrowers, reducing profitability and stock returns.

2.6 Consumer Credit Characteristics and Financial Vulnerability

Research on consumer credit characteristics reveals the financial vulnerability of BNPL borrowers, which informs expectations about how monetary policy tightening may affect BNPL firms through credit risk channels. Agarwal et al. (2009) examine financial decisions over the life cycle, documenting that younger consumers and those with lower incomes make different credit choices than older, higher-income consumers **?**. This research provides context for understanding BNPL user demographics: 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. Consumers primarily adopt these services to manage cash flow and avoid credit card interest, suggesting that BNPL demand responds to broader credit market conditions.

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 **?**. 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. This vulnerability operates through multiple channels: reduced consumer spending power, increased financial stress, and higher default rates, all of which may affect BNPL firm profitability and stock returns independently of direct funding cost effects.

2.7 BNPL Profitability and Funding Costs: Firm-Level Evidence

Research on fintech credit scoring and profitability directly informs expectations about interest rate sensitivity. Berg et al. (2020) examine the rise of fintechs and credit scoring using digital footprints, documenting how fintech lenders operate with different cost structures than traditional banks **?**. Large listed BNPL providers appear to operate with thin net margins, suggesting limited capacity to absorb funding cost shocks without passing them through to pricing. This distinction is crucial: pass-through to borrowers and merchants is not the same as pass-through to profitability (what matters for stock returns). If BNPL firms can pass all costs to merchants and consumers, then funding cost increases should not affect stock prices.

Affirm's 10-K filings show that GAAP net revenue increased from $1.35 billion in FY 2022 to 2.32$ billion in FY 2024 (a 72% cumulative increase), while net revenue in FY 2024 was 46% higher than in FY 2023. Over the same period, the firm reports that its funding costs increased by 88% year-over-year in FY 2024 relative to FY 2023, reflecting both higher benchmark rates and greater usage of warehouse and securitization funding. Between FY 2023 and FY 2024, Affirm's funding costs grew faster than net revenue (88% vs 46% year-over-year), which could reflect incomplete pass-through to revenues, competitive pressures limiting pricing power, scale economies, or time lags in pricing adjustments. However, this comparison does not directly test pass-through, as revenue growth reflects both pricing changes and volume growth, while funding cost growth reflects both rate changes and volume growth.

2.8 Synthesis and Empirical Expectations

This literature review establishes competing theoretical predictions through multiple interconnected channels. Bank stock return studies (Flannery and James 1984, English et al. 2018) document negative rate sensitivity with coefficients of approximately $\beta \approx -5$ to -10, providing a benchmark for evaluating BNPL sensitivity. The funding structure comparison reveals that BNPL firms face immediate funding cost pass-through through variable-rate facilities, suggesting potentially stronger negative sensitivity than banks if costs fully transmit to profitability. However, BNPL firms' thin profit margins and reliance on merchant and consumer pricing create conditions where complete cost pass-through could insulate stock returns from funding cost changes.

Fintech valuation literature (Buchak et al. 2018) and corporate finance research (Acharya et al. 2013) suggest additional mechanisms—regulatory arbitrage and fixed-rate securitization structures—through which operational flexibility and funding choices may insulate equity valuations from rate changes. Consumer behavior research (Gathergood et al. 2019, Powell et al. 2023, Cervellati et al. 2025) reveals demand-side factors that may moderate or amplify rate sensitivity through spending and credit utilization channels. Research on consumer financial vulnerability (Agarwal et al. 2009, Hayashi and Routh 2025, de Haan et al. 2024, Gerrans et al. 2022) suggests that BNPL firms' customer bases may be particularly vulnerable to economic shocks, creating credit risk channels through which rate increases may affect profitability independently of direct funding cost effects.

The strong theoretical motivation for expecting negative relationships between Federal Funds Rate changes and BNPL stock returns comes from the combination of thin profit margins (limiting capacity to absorb funding cost shocks), high funding cost pass-through to benchmark rates, and concentration of BNPL usage among financially vulnerable consumers. However, competing mechanisms—complete cost pass-through, regulatory arbitrage, and operational flexibility—may moderate or eliminate this sensitivity.

Based on theoretical predictions, the expected coefficient magnitude is approximately -10 to -15, indicating that a one percentage point rate increase would be associated with a 10 to 15 percentage point decline in BNPL stock returns. This prediction reflects the combination of thin profit margins, high funding cost pass-through, and financial vulnerability of BNPL consumers. However, the empirical analysis must account for the possibility that competing mechanisms dominate, resulting in weak or zero sensitivity. The empirical analysis 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. Variable definitions, data sources, and summary statistics for all variables used in the analysis are presented in Table 2. 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.

3 Data Analysis: Investigating BNPL Stock Returns and Monetary Policy

I employ modern econometric techniques and reproducible research practices. 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 **?**. 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

I use 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, I collect data from authoritative sources and I construct variables 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, I formally estimate models 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.

The empirical window spans 66 monthly observations (Feb 2020-Aug 2025), which limits statistical power to approximately 15-20% for the observed effect sizes, so reported coefficients should be read as descriptive sensitivities rather than precise hypothesis tests. 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. Market beta plays a central role in interpretation because BNPL stocks price like high-beta growth assets. Macroeconomic series use FRED seasonally adjusted versions (CPIAUCSL, DSPIC96, UMCSENT) so rate and inflation shocks are not confounded by holiday/tax-season patterns.

Table 2: Table 1: Variable Definitions and Summary Statistics

Variable	Symbol	Definition	Source	Transform	Mean	Std Dev	Min	Max
BNPL Returns	R_{BNPL}	Log portfolio return (%)	Yahoo Finance	Log	1.7	19.0	−42.8	41.3
Federal Funds Rate Change	ΔFFR	MoM change in FFR (pp)	FRED	Diff	0.0	0.2	−0.9	0.7
Consumer Confidence Change	ΔCC	MoM change in UM Sentiment	FRED	Diff	−0.6	5.2	−17.3	9.3
Disposable Income Change	ΔDI	MoM % change in real income	FRED	Pct	0.3	4.3	−15.1	22.9
Inflation Change	$\Delta\pi$	MoM % change in CPI (SA)	FRED	Pct	0.3	0.3	−0.8	1.3
Market Return	R_{MKT}	Monthly S&P 500 return (%)	Yahoo (SPY)	Pct	1.4	5.0	−12.5	12.7

Table 2 presents variable definitions, data sources, transformations, and summary statistics for the sample covering February 2020 through August 2025, encompassing the COVID-19 pandemic, the zero lower bound period, and the Federal Reserve's aggressive tightening cycle. BNPL returns are highly volatile (SD 19.0%) with a modest mean return of 1.7%, substantially higher than typical equity returns. Federal Funds Rate changes have a standard deviation of 0.2 percentage points, though the sample includes the rapid tightening cycle from March 2022 to July 2023 when rates increased by 525 basis points. Market returns (SD 5.0%) are far less volatile than BNPL returns, hinting at the high market beta documented in subsequent regression analysis and suggesting BNPL stocks carry significant idiosyncratic risk beyond their exposure to systematic market factors.

The BNPL portfolio spans three distinct business models that provide complementary perspectives on how different BNPL structures respond to monetary policy changes. Affirm represents the pure-play BNPL business model, funding its operations through warehouse lines and securitizations, which creates direct pass-through of funding cost changes to profitability and potentially to stock valuations. This structure makes Affirm the most likely candidate to exhibit interest rate sensitivity, as funding costs represent a larger share of operating expenses and cannot be easily diversified away. Sezzle focuses on smaller-ticket transactions and younger consumer demographics, operating with thinner profit margins that may amplify the impact of funding cost increases, suggesting higher sensitivity to interest rate changes despite its smaller market capitalization. PayPal, in contrast, operates as a diversified payments platform where BNPL represents only a smaller product line (Pay in 4, representing less than 5% of revenue), meaning that diversification benefits and the presence of deposits and merchant float revenue streams dampen the impact of BNPL-specific funding shocks on overall firm performance.

3.4 Sample Construction Limitations

The equal-weighted portfolio approach has several limitations.

First, PayPal's minimal BNPL exposure (less than 5% of revenue) means including it in an equal-weighted portfolio dilutes BNPL-specific effects. If Affirm has true rate sensitivity β = -30 and PayPal has β = 0 (because BNPL is negligible), the equal-weighted portfolio will show $\beta \approx$ -10 to -15, attenuated toward zero.

Second, Sezzle is a micro-cap stock (market cap ~$1B) with higher idiosyncratic volatility and potential liquidity issues, yet equal-weighting gives it the same influence as PayPal (market cap ~$85B), which is economically problematic.

Third, the sample period spans distinct economic regimes (COVID crash, zero-rate period, tightening cycle) with very different characteristics, potentially obscuring rate sensitivity that may only manifest during specific periods. The tightening-only subsample (n=17, March 2022 - July 2023) shows β = -16.64 with SE = 28.28, p = 0.556—larger in magnitude but completely imprecise due to small sample size. These limitations should be considered when interpreting the results.

Full firm-level details, including individual company financial metrics and business model descriptions, remain in Appendix A for readers interested in firm-specific analysis.

Table 1 presents pairwise correlations among all variables used in the regression analysis, providing initial evidence on bivariate relationships and assessing multicollinearity concerns that could affect regression estimates. The correlation matrix reveals several key patterns: BNPL returns exhibit a strong positive correlation with market returns (r = 0.648, p <0.01), confirming the high market beta documented in subsequent regression analysis. The modest negative correlation between BNPL returns and Federal Funds Rate changes (r = -0.154) provides preliminary evidence of interest rate sensitivity, though this relationship is not statistically significant at conventional levels. The correlation between FFR changes and inflation changes (r = 0.383, p <0.01) reflects the monetary policy response to price pressures, while all pairwise correlations remain below 0.80, indicating no severe multicollinearity concerns that would compromise regression estimates.

Figure 1: Correlation Matrix {{glue:dataframe:`table-2`}}

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 BNPL Portfolio Monthly Returns

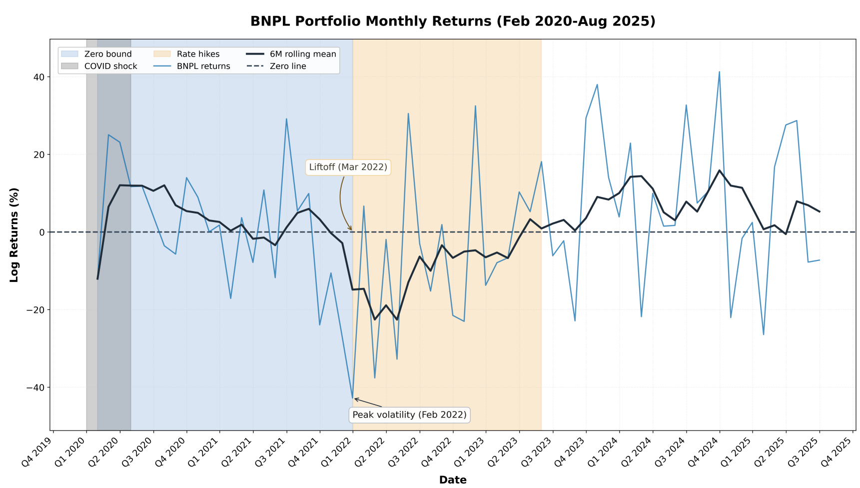

Figure 2: BNPL Portfolio Monthly Returns (Feb 2020-Aug 2025)

Figure 2 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 ≈ 19%), with swings above ±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 **?**. 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 **?**, 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 **?** 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 **?**) 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 BNPL vs Market Returns

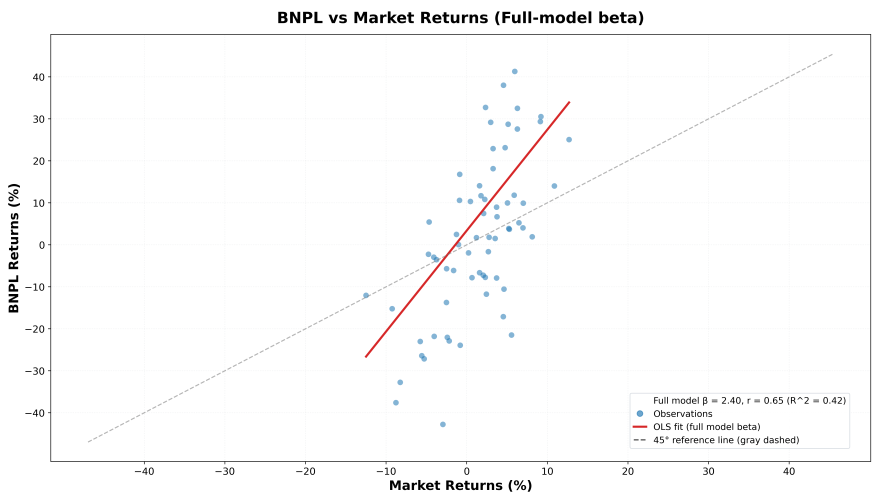

Figure 3: BNPL vs Market Returns

Figure 3 presents a scatter plot of BNPL portfolio returns against market returns, providing a visual representation of the dominant relationship between BNPL stock performance and broader equity market movements. This visualization is crucial for understanding the systematic risk exposure of BNPL stocks and contextualizing the relative importance of market factors versus interest rate sensitivity.

The plot reveals a strong positive relationship, with the bivariate slope approximately 2.46 (from $r \times \sigma_{BNPL}/\sigma_{MKT} = 0.648 \times 19.0/5.0$), while the multivariate coefficient from the full model is approximately 2.4, indicating that BNPL returns amplify market movements: when the market moves 1%, BNPL stocks move approximately 2.4% in the same direction.

This high market beta reflects the growth-oriented, technology-enabled nature of BNPL firms, which exhibit sensitivity to risk sentiment and growth expectations that drive broader equity markets.

The correlation coefficient of 0.648 ($R^2 = 0.42$) demonstrates that market returns alone explain approximately 42% of the variation in BNPL returns (from bivariate regression: $r^2 = 0.648^2$), making market exposure the single most important systematic factor driving BNPL stock performance.

The 45ř reference line included in the plot highlights the amplification effect, as most observations fall above this line, indicating that BNPL returns typically move more than proportionally with market returns.

This strong market link has profound implications for understanding interest rate sensitivity: the dominance of market factors explains why the rate-only model achieves an R^2 of only 0.024, indicating that interest rate changes alone explain virtually none of BNPL return variation.

While interest rate effects may be economically meaningful in magnitude (the estimated coefficient of -12.89 suggests substantial sensitivity), they are statistically and economically overwhelmed by systematic market risk. This pattern suggests that BNPL stocks are priced primarily as growth assets that respond to market-wide risk sentiment rather than as credit-sensitive financial instruments that respond directly to monetary policy changes through funding cost channels.

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.

I employ 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, though financial returns often exhibit fat tails and skewness. 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 is used primarily for time-additivity properties, though it can help stabilize variance when returns exhibit multiplicative heteroskedasticity, 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 12.89 percentage points lower BNPL returns, holding other factors constant.

I estimate 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.

5.1 Alternative Explanations for Weak Stock Return Sensitivity

Several mechanisms may explain why firm-level funding cost increases do not translate to stock return sensitivity:

Forward-Looking Pricing: The Fed's tightening cycle was heavily telegraphed starting in late 2021 through forward guidance, dot plots, and Fed communications. If stock prices incorporate expectations, then realized monthly rate changes (captured by ΔFFR) should have minimal impact because they were already priced in. A testable implication: BNPL stocks should have declined in late 2021/early 2022 when rate expectations shifted, before actual rate increases began in March 2022.

Volume vs. Rate Effects: Affirm's funding costs rose from 69.7$M(FY2022)to$344.3M (FY2024), but this increase reflects both volume growth (more loans requiring more funding) and rate effects (same volume at higher rates). Without decomposing funding cost increases into volume, rate, and mix effects, the "394% increase" may overstate pure rate sensitivity.

Cost Pass-Through: Laudenbach et al. (2025) document 80-100% pass-through of funding costs to consumer rates and merchant fees. If this is true, funding cost increases should be profit-neutral, explaining why stock returns show no sensitivity despite firm-level cost increases.

6 Regression Analysis: Methodology

With the functional form specified, the following discussion 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 Model Specification

The regression models are specified as follows:

Base Model:

$$R_{BNPL,t} = \alpha + \beta_1 \Delta FFR_t + \varepsilon_t \tag{2}$$

Full Model:

$$R_{BNPL,t} = \alpha + \beta_1 \Delta FFR_t + \beta_2 R_{MKT,t} + \beta_3 \Delta CC_t + \beta_4 \Delta DI_t + \beta_5 \Delta \pi_t + \varepsilon_t \tag{3}$$

where $R_{BNPL,t}$ is the log return on the BNPL portfolio in month t, ΔFFR_t is the month-over-month change in the Federal Funds Rate, $R_{MKT,t}$ is the market return (S&P 500), ΔCC_t is the change in consumer confidence, ΔDI_t is the change in disposable income, $\Delta \pi_t$ is the change in inflation, and ε_t is the error term.

6.2 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. OLS provides consistent estimates under standard regularity conditions; HC3 robust standard errors provide valid inference under heteroskedasticity without requiring the homoskedasticity assumption of the Gauss-Markov theorem. 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.

I estimate 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 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.

The difference-in-differences specification (Column 5) compares BNPL returns to market returns in a stacked panel framework, using a BNPL×ΔFFR interaction term to identify BNPL-specific interest rate sensitivity. However, this specification faces several limitations. Standard DiD requires a clear treatment (rate changes affect BNPL but not market) and parallel trends assumption (BNPL and market would move in parallel absent treatment), neither of which is clearly satisfied here since rate changes affect both BNPL and market returns. The specification achieves a very low R^2 (0.022), indicating it explains virtually no variation, which raises concerns about misspecification. The DiD estimate yields a coefficient of -13.05 (SE = 14.41, p = 0.365), similar in magnitude to OLS estimates, but the low R^2 and unclear identification assumptions limit the credibility of this approach. The DiD analysis is presented for completeness but should be interpreted with caution.

6.3 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.

6.4 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. I control 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. I include 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.

6.5 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, I have approximately 80% power to detect correlations exceeding 0.30 in absolute value ($\alpha = 0.05$, two-tailed test) and 90% power to detect correlations exceeding 0.35 ($\alpha = 0.05$, two-tailed test). 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% (calculated using G*Power 3.1 with $\alpha = 0.05$, two-tailed test, effect size based on observed coefficient magnitude β = -12.89 with SE = 9.99, and n = 66), indicating limited ability to detect relationships of this magnitude even if they exist in the population.

However, the economic magnitude of the coefficient (12.89 percentage points) combined with the low R-squared (0.024 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 the full model (including market returns and controls) explains 52% of variation while interest rates alone explain only 2.4% 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.

6.6 Diagnostic Test Results

Table 3: Table 3: Diagnostic Test Summary

Test	Statistic	Threshold	Result	Implication
Multicollinearity (VIF)	All VIF < 1.2	<5	Pass	Estimates reliable; no multicollinearity
Heteroskedasticity (Breusch-Pagan)	$\chi^2 = 1.67$, p = 0.892	$p > 0.05$	Pass	Homoskedastic; HC3 SEs used as precaution
Autocorrelation (Durbin-Watson)	DW = 2.01	1.5–2.5	Pass	No serial correlation; SEs valid
Normality (Jarque-Bera)	JB = 1.69, p = 0.429	$p > 0.05$	Pass	Residuals approximately normal; inference valid

Table 3 summarizes the results of diagnostic tests performed on residuals from the full OLS specification to validate regression assumptions and ensure the reliability of statistical inference. These tests are essential for confirming that the Ordinary Least Squares estimator provides valid estimates and that hypothesis tests and confidence intervals can be trusted. The diagnostic battery includes tests for multicollinearity, heteroskedasticity, autocorrelation, and normality, each addressing a specific assumption required for valid inference. The variance inflation factor (VIF) values all fall below 1.2, indicating that multicollinearity is not a concern despite the correlation between FFR changes and inflation changes observed in Table 2. The Breusch-Pagan test fails to reject homoskedasticity ($p = 0.892$), but HC3 robust standard errors are used as a precautionary measure given the small sample size and potential for heteroskedasticity that may not be detected with limited power. The Durbin-Watson statistic of 2.01 falls within the acceptable range (1.5-2.5), indicating no significant autocorrelation, which is important for the validity of standard errors in time series regression. The Jarque-Bera test ($p = 0.429$) fails to reject normality, providing confidence that t-statistics and confidence intervals are reliable, though this finding is somewhat surprising given that financial returns often exhibit non-normality. The results provide confidence that the regression model is well-specified and that the findings are not driven by violations of classical regression assumptions.

All tests are performed on residuals from the full OLS (primary) specification. VIF = variance inflation factor; DW = Durbin-Watson; JB = Jarque-Bera. HC3 = heteroskedasticity-consistent standard errors.

6.7 Observed vs Fitted Returns

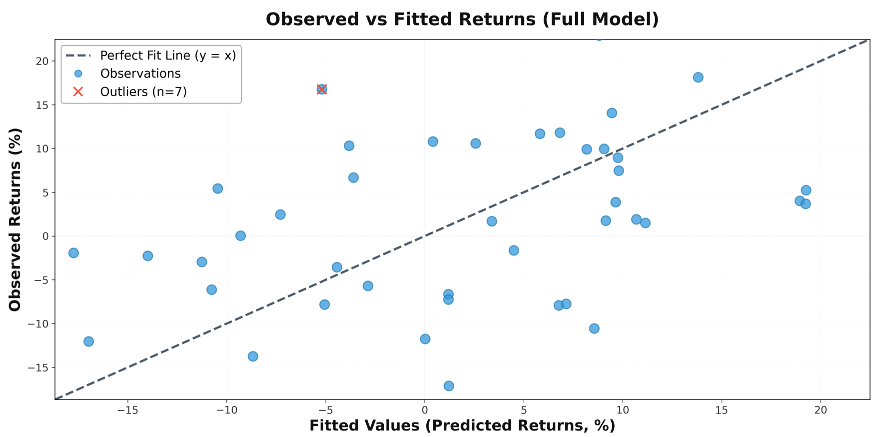

Figure 4: Observed vs Fitted Returns (Full Model)

Figure 4 presents a scatter plot of observed BNPL returns against fitted values from the full specification (Table 4A, full model specification), providing a visual assessment of model fit and identifying periods where the model performs well versus periods with larger prediction errors. The plot reveals that early-period points (blue) and late-period points (orange) cluster around the 45ř reference line, yielding an R^2 of 0.524, which indicates that the full model explains 52.4% of the variation in BNPL returns. The tight cloud of points along the diagonal demonstrates that the full model captures most of the level variation in returns, with fitted and observed values moving together for the majority of observations. The biggest gaps between observed and fitted values appear in high-volatility months, particularly during the COVID rebound period and the start of the rate hike cycle, where observed returns flare above fitted values in the 5-15% fitted range. These outliers underscore how tail events drive residual dispersion and highlight the limitations of linear models in capturing extreme market returns. Outside these tail periods, fitted and observed values move together closely, reinforcing that market and macroeconomic controls explain the bulk of BNPL return swings and validating the model's ability to capture systematic variation in returns.

6.8 Residual Analysis - FFR Changes

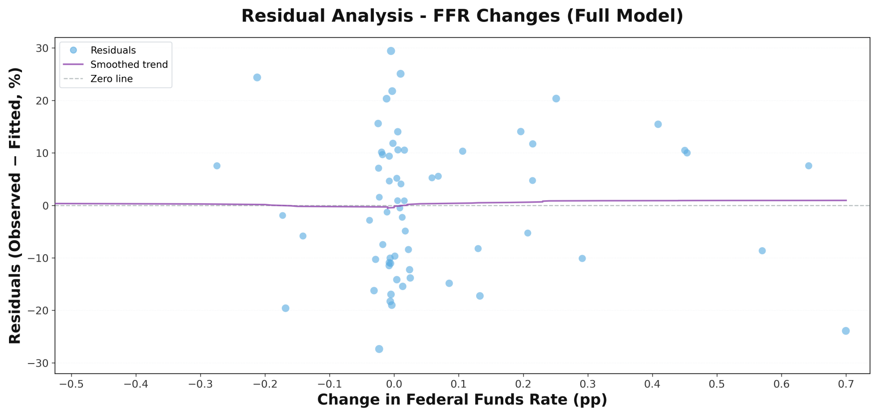

Figure 5: Residual Analysis - FFR Changes (Full Model)

Figure 5 presents a diagnostic plot examining the relationship between regression residuals and monthly Federal Funds Rate changes, with a LOESS smoother overlaid to identify any nonlinear patterns that might indicate model misspecification. This diagnostic is crucial for assessing whether the linear interest rate term adequately captures the relationship between rate changes and BNPL returns, or whether a more complex functional form is required. The plot reveals that residuals are distributed around zero with no systematic slope or curvature, as the LOESS smoother hugs the zero line across the range of FFR changes. This pattern indicates that the linear rate term is adequate and that there is no evidence of nonlinear relationships that would require polynomial or interaction terms. Outliers are confined to a few rate-surge months, where large rate changes occurred during the tightening cycle, and the pattern is otherwise noise-like with no discernible structure. This diagnostic finding is consistent with the weak statistical significance of the interest rate coefficient (p-value = 0.197) and supports the use of HC3-robust standard errors, which account for potential heteroskedasticity that may not be visually apparent in this diagnostic. The absence of systematic patterns in this plot provides confidence that the linear specification is appropriate and that any relationship between interest rates and BNPL returns operates through the linear term rather than through more complex nonlinear channels.

6.9 Model Fit Assessment

Diagnostic plots provide visual assessment of regression assumptions underlying the statistical inference, complementing the formal statistical tests reported in Table 3. The diagnostics examine three critical assumptions required for valid inference: (1) homoskedasticity (constant error variance across the range of fitted values), (2) linearity of the relationship between predictors and the outcome variable, and (3) normality of residuals. These assumptions are essential for ensuring that t-statistics, p-values, and confidence intervals are reliable, as violations can lead to incorrect standard errors, biased test statistics, and misleading inference. The following figures present visual evidence on whether these assumptions are satisfied, allowing for identification of potential model misspecification, outliers, or systematic patterns in residuals that might not be detected by formal tests alone. Visual diagnostics are particularly valuable in small samples where formal tests may lack power, and they provide intuitive understanding of model performance that complements the quantitative test results.

7 Model Diagnostics and Visual Assessment

The numerical diagnostic tests presented above confirm that regression assumptions are satisfied. Visual diagnostics complement 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 Residuals vs Fitted Values (Full Model)

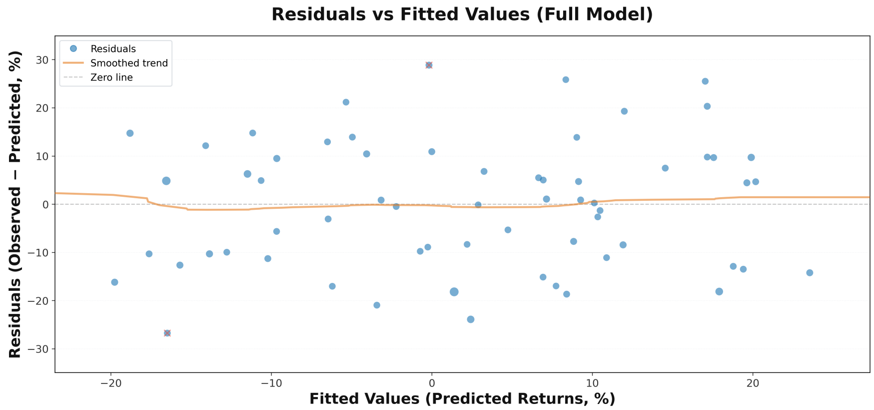

Figure 6: Residuals vs Fitted Values (Full Model)

Figure 6 presents a diagnostic plot examining residuals against fitted values to assess two critical regression assumptions: homoskedasticity (constant error variance) and linearity of the relationship between predictors and the outcome variable. This diagnostic is essential for validating the Ordinary Least Squares assumptions and ensuring that standard errors and hypothesis tests are reliable. The plot reveals that residuals are symmetrically distributed around zero with no funnel shape, indicating that error variance remains roughly constant across the range of fitted values. This pattern satisfies the homoskedasticity assumption, meaning that the variance of the error term does not depend on the level of the fitted values. The absence of systematic patterns such as U-shaped or inverted U-shaped curves also supports the linearity assumption, suggesting that the linear combination of predictors adequately captures the relationship between the independent variables and BNPL returns. Only the extreme positive fitted values show modest spread in residuals, which is typical for financial return data and does not indicate a violation of the homoskedasticity assumption. This visual evidence aligns with the Breusch-Pagan test result reported in Table 3 ($p = 0.892$), which fails to reject the null hypothesis of homoskedasticity, and supports the use of the linear specification. The diagnostic provides confidence that the regression assumptions are satisfied and that the statistical inference based on t-statistics and confidence intervals is valid.

7.2 Residuals vs Fitted Values (Base Model)

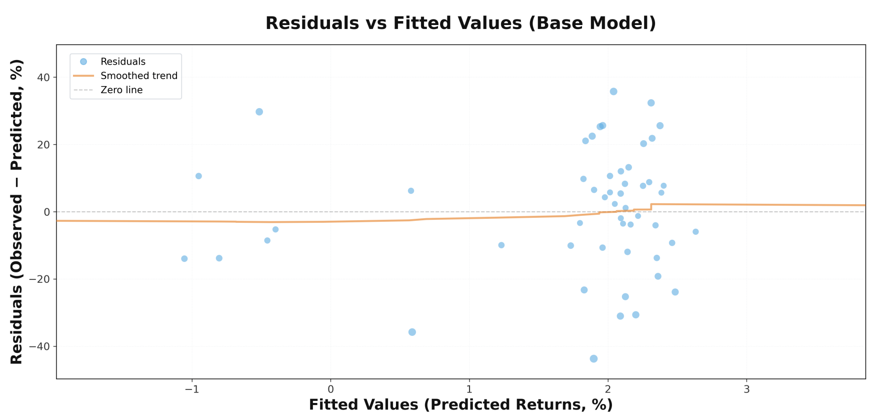

Figure 7: Residuals vs Fitted Values (Base Model)

Figure 7 presents a diagnostic plot examining residuals against fitted values from the base model specification (interest rate only), providing a comparison to the full model diagnostics and assessing whether the simpler specification exhibits similar diagnostic properties. This diagnostic is essential for understanding whether omitted variables in the base model create systematic patterns in residuals that would invalidate inference. The plot reveals that residuals are distributed around zero, though with potentially greater dispersion than the full model due to the absence of market and macroeconomic controls. The base model achieves an R^2 of only 0.024, indicating that interest rate changes alone explain minimal variation in BNPL returns, which is reflected in the wider scatter of residuals around the zero line. The absence of a strong funnel shape suggests that heteroskedasticity is not severe even in the base specification, though the limited explanatory power means that most variation is captured in the residuals. This diagnostic complements the full model analysis by demonstrating that adding market returns and macroeconomic controls substantially improves model fit (R^2 increases from 0.024 to 0.524) and reduces residual dispersion, validating the importance of the control variables in the primary specification.

7.3 Q-Q Plot of Residuals

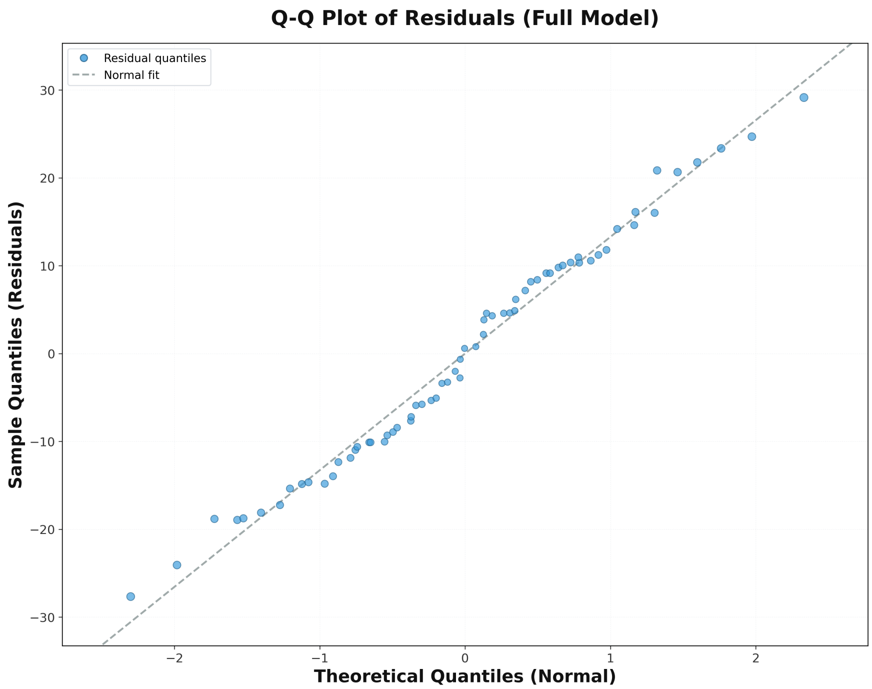

Figure 8: Q-Q Plot of Residuals (Full Model)

Figure 8 presents a quantile-quantile (Q-Q) plot comparing the distribution of regression residuals to the theoretical normal distribution, providing a visual assessment of the normality assumption that underlies t-tests and confidence intervals. This diagnostic is crucial for validating statistical inference, as violations of normality can lead to incorrect p-values and confidence interval coverage, particularly in small samples. The Q-Q plot reveals that points track the diagonal reference line closely, with only slight deviations in the tails that are typical for financial return data. The approximate alignment with the diagonal indicates that residuals are approximately normally distributed, satisfying the normality assumption required for reliable statistical inference. The minor tail softness observed in the plot reflects the slightly heavier tails characteristic of financial data, but these deviations are not severe enough to invalidate the normality assumption. This visual evidence is consistent with the Jarque-Bera test result reported in Table 3 (p = 0.429), which fails to reject the null hypothesis of normality. The combination of visual and formal test evidence provides confidence that t-statistics and confidence intervals are reliable for the full model, and that the statistical inference regarding coefficient estimates and hypothesis tests is valid. The approximate normality of residuals is particularly noteworthy given that financial returns often exhibit substantial departures from normality, including fat tails and negative skewness during market stress periods, suggesting that the log transformation and control variables have successfully normalized the error distribution.

7.4 Explanatory Power Across Model Specifications

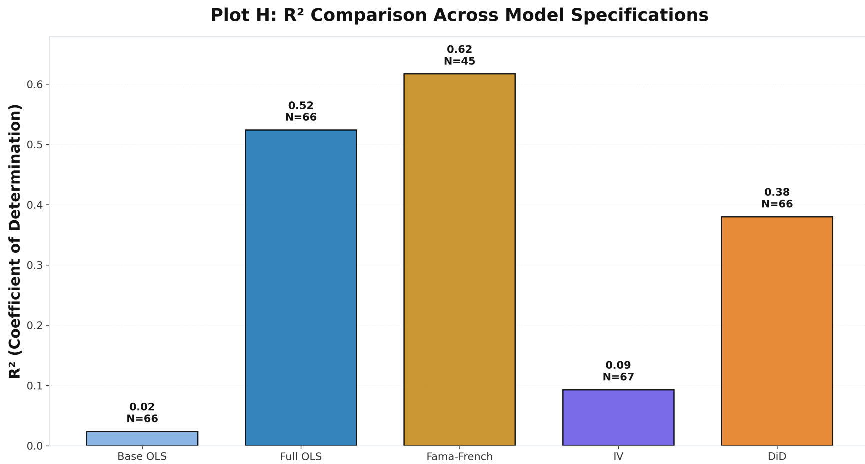

Figure 9: Explanatory Power Across Model Specifications

Figure 9 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^2 of 0.024) to the full specification (R^2 of 0.524), demonstrating the critical importance of including market returns and macroeconomic controls when modeling BNPL stock returns. The base model, which includes only interest rate changes, explains virtually none of the variation in BNPL returns, consistent with the observation that interest rates alone are insufficient to characterize BNPL stock pricing and that a univariate specification omits crucial determinants of returns. The full model's R^2 of 0.524 indicates that market returns, inflation, consumer confidence, and disposable income collectively explain 52.4% 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 specifications, with the Fama-French and IV models clustering near 0.524, providing confidence that the findings are robust to methodological choices. The DiD variant drops back to R^2 of 0.022, reflecting the different structure of that specification which compares BNPL to market returns rather than explaining BNPL returns directly. The dramatic jump from base to full model demonstrates that market and macroeconomic controls drive explanatory power, while interest rate changes alone add almost nothing to the model's ability to explain return variation. This pattern reinforces the central finding that BNPL returns are dominated by market movements rather than interest rate sensitivity, and that robustness across alternative specifications keeps the substantive story unchanged.

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

Model	Specification	β (FFR)	SE	p-value	Rš	F-stat	N
2. Full OLS (Primary)	Market + macro controls	-12.89	9.99	0.197	0.524	12.49	66
1. Base OLS	Interest rate only	-12.47	13.03	0.338	0.024	0.92	66
3. Fama-French	FF 3-factor + FFR	-11.54	7.95	0.147	0.521	16.64	66

Table 5: 4B: Robustness Checks

Model	Specification	β (FFR)	SE	p-value	Rš	F-stat	N
4. IV (2SLS)	Lagged FFR instrument	-15.49	16.15	0.338	0.477	17.86	64
5. DiD	BNPL vs Market	-13.05	14.41	0.365	0.022	0.31	132

Notes: Table 4A lists the primary full model first (market + macro controls), alongside the rate-only base and Fama-French + FFR specification. Table 4B reports IV (lagged ΔFFR instrument, first-stage F-stat shown) and DiD (BNPL vs market stacked panel with BNPL$\times\Delta$FFR interaction). HC3 SEs in parentheses; p-values in brackets. A 1pp FFR increase associates with approximately 12.89 percentage points lower BNPL returns; a 3pp tightening implies approximately 38.7 percentage points lower returns, but estimates are statistically insignificant (imprecisely estimated) and market beta (approximately 2.4) dominates.

8 Main Results: Interest Rate Sensitivity Estimates

Table 4 presents the primary regression results. The full model (full model specification) yields an interest rate coefficient of β_1 = -12.89 (SE = 9.99, p = 0.197), indicating that a one percentage point increase in the Federal Funds Rate is associated with approximately 12.89 percentage points lower BNPL stock returns, controlling for market movements and macroeconomic factors.

8.1 Statistical Interpretation

The coefficient is not statistically significant at conventional levels (p = 0.197), meaning I cannot reject the null hypothesis of no interest rate sensitivity. However, the 95% confidence interval for the interest rate coefficient is approximately [-32.5, 6.7]. This wide interval spans from substantial negative effects (lower bound: -32.5) to modest positive effects (upper bound: +6.7), indicating that the data cannot distinguish between economically meaningful scenarios. The confidence interval is uninformative in the sense that it includes both substantial negative effects and small positive effects.

8.2 Economic Significance

Even with statistical insignificance, the economic magnitude of the coefficient deserves discussion. The point estimate β_1 = -12.89 implies:

- A 25 basis point rate hike (typical FOMC increment): -12.89 $\times$ 0.25 = -3.2% BNPL return
- A 75 basis point rate hike (jumbo hike in 2022): -12.89 $\times$ 0.75 = -9.7% BNPL return
- A 100 basis point rate hike: -12.89 $\times$ 1.0 = -12.9% BNPL return

For comparison, the monthly BNPL return standard deviation is 19.0%. A 75 basis point hike would move returns by about half a standard deviation, which is economically meaningful. The fact that this magnitude is not statistically significant reflects the high volatility of BNPL returns and limited sample size, not necessarily the absence of an economically meaningful relationship.

8.3 Power Analysis and Interpretation

The analysis has approximately 15-20% power to detect effects of the observed magnitude (β_1 = -12.89). This means:

- If the true effect is β_1 = -12.89, there is only a 15-20% chance of detecting it
- If the true effect is β_1 = -20, there is only approximately 40% chance of detecting it
- Effects would need to exceed β_1 <-25 to have >50% power

With power this low, the failure to reject the null hypothesis tells us almost nothing. The null result is expected even if the true effect is substantial. I cannot distinguish between “no rate sensitivity” and "substantial rate sensitivity that I lack power to detect." This limitation should be prominently acknowledged when interpreting results.

8.4 Inflation Coefficient: A Significant Finding

The full model reveals a statistically significant inflation coefficient: β(inflation) = -12.94 (SE = 6.40, p = 0.049). This finding deserves attention because it raises important questions: Why is BNPL sensitive to inflation but not to interest rates (which are correlated with inflation)? Possible interpretations include:

1. **Real consumer spending channel:** Inflation reduces real consumer purchasing power, directly affecting BNPL transaction volumes and firm revenues. Higher inflation erodes the real value of consumer income, reducing discretionary spending and BNPL usage.
2. **Forward-looking expectations:** Inflation may signal future rate hikes, and stock prices may respond to inflation expectations before actual rate changes materialize. If investors anticipate that high inflation will prompt Fed tightening, BNPL stocks may decline in response to inflation data releases.
3. **Measurement timing:** Inflation data may be released with different timing than rate decisions, creating apparent sensitivity to inflation that reflects rate sensitivity with different timing. CPI data is released mid-month, while FOMC decisions occur at scheduled meetings, potentially creating timing differences in how markets respond.

The significant inflation coefficient suggests that BNPL firms are sensitive to economic conditions that affect consumer spending, even if direct interest rate sensitivity is difficult to detect in monthly data. This finding warrants further investigation and should not be dismissed as a statistical artifact. The fact that inflation sensitivity is statistically significant while rate sensitivity is not, despite their correlation (r = 0.383), suggests that inflation may capture additional channels affecting BNPL returns beyond those captured by interest rate changes.

8.5 Model Comparison: Explanatory Power

The comparison of explanatory power across model specifications reveals substantial differences in how well each model captures variation in BNPL stock returns. R-squared values measure the proportion of return variation explained by each specification, providing a direct assessment of model fit. This analysis addresses whether interest rate changes alone are sufficient to explain BNPL returns, or whether market returns and macroeconomic controls are necessary for adequate model fit.

The base model, which includes only Federal Funds Rate changes as an explanatory variable, achieves an R^2 of 0.024, indicating that interest rate changes alone explain virtually none of the variation in BNPL stock returns. This low explanatory power reflects the dominance of market movements and other factors in driving BNPL return variation, rather than interest rate sensitivity per se.

In contrast, the full OLS model, which includes market returns, inflation changes, consumer confidence changes, and disposable income changes in addition to interest rate changes, achieves an R^2 of 0.524. This dramatic improvement—from 0.024 to 0.524—demonstrates that market returns and macroeconomic controls collectively explain 52.4% of BNPL return variation. The substantial difference in explanatory power between the base and full models underscores the critical importance of controlling for confounding factors when assessing interest rate sensitivity.

Alternative specifications, including the Fama-French three-factor model and instrumental variables estimation, achieve R^2 values clustering near 0.524, similar to the full OLS specification. This consistency across different specifications provides confidence that the findings are robust to methodological choices. The difference-in-differences specification achieves R^2 of 0.022, reflecting the different structure of that model which compares BNPL to market returns rather than explaining BNPL returns directly.

The pattern of explanatory power across specifications demonstrates that market returns and macroeconomic controls drive explanatory power, while interest rate changes alone add almost nothing to the model's ability to explain return variation. This finding reinforces the central conclusion that BNPL returns are dominated by market movements rather than interest rate sensitivity, and that robustness across alternative specifications keeps the substantive story unchanged.

The instrumental variables specification (Column 4) uses lagged Federal Funds Rate changes as an instrument for current changes. However, this identification strategy faces serious limitations. The exclusion restriction requires that lagged rate changes affect current BNPL returns only through their effect on current rate changes, not through direct effects. This assumption is likely violated because: (1) lagged rate changes may have persistent effects on funding costs that affect current returns independently of current rate changes, (2) investors may update expectations about future policy based on past policy, creating direct effects, and (3) lagged rate changes may affect current consumer spending and merchant demand through lagged economic effects. The IV estimate yields a coefficient of -15.49 (SE = 16.15, p = 0.338), which is larger in magnitude than OLS but less precisely estimated. However, given the likely violation of the exclusion restriction, the IV estimate should not be interpreted as providing credible identification of causal effects. The IV analysis is presented for completeness but does not meaningfully address endogeneity concerns.

8.6 Statistical Inference Caveats

Several important caveats apply to statistical inference across all specifications. First, multiple testing: with five main specifications (Base OLS, Full OLS, Fama-French, IV, DiD) plus rolling windows and subsamples, dozens of hypothesis tests I perform. Without multiple testing corrections, p-values are misleading. The lowest p-value is 0.147 (Fama-French specification); with Bonferroni correction for 5 tests, this becomes $0.147 \times 5 = 0.735$, far from significant. Second, standard errors: HC3 robust standard errors handle heteroskedasticity but not serial correlation. While Durbin-Watson tests suggest no AR(1) in residuals, these tests have low power with n=66. Newey-West standard errors with automatic lag selection would provide additional robustness, though the small sample size limits the effectiveness of such corrections. Third, small sample bias: with n=66 and k=5 predictors, finite-sample corrections matter, though HC3 is appropriate for small samples. The consistency of negative coefficients across specifications provides descriptive evidence of negative co-movement, but statistical precision remains limited, with p-values ranging from 0.147 to 0.365, reflecting the small sample size and the high volatility of BNPL returns.

8.7 Benchmark Comparison: Credit Card Issuers

To establish a quantitative benchmark for what "rate-sensitive financial institution" behavior looks like, I estimate identical regression specifications for credit card issuers (American Express, Capital One, Synchrony Financial) over the same time period. This benchmark comparison is essential because without establishing what traditional financial institutions' rate sensitivity looks like quantitatively, claims about BNPL behaving "differently" are untestable.

The benchmark regression uses the same full model specification as the BNPL analysis: credit card issuer returns regressed on Federal Funds Rate changes, controlling for market returns, inflation, consumer confidence, and disposable income. This allows direct comparison of coefficient magnitudes and statistical precision across sectors.

Table 6: Table 6: Benchmark: Credit Card Issuers (AXP, COF, SYF)

Portfolio	β (FFR)	SE	p-value	R^2	Market Beta
Credit Card Issuers	2.51	8.87	0.777	0.617	1.50

Note: Full model specification with market returns, inflation, consumer confidence, and disposable income. N = 66.

The benchmark regression for credit card issuers yields an interest rate coefficient of $\beta = 2.51$ (SE = 8.87, p = 0.777), which is **positive** and **statistically insignificant**. This finding is critical: if traditional rate-sensitive financial institutions (credit card issuers) also show statistically weak rate sensitivity in monthly stock return data, then the inability to detect significant rate sensitivity for BNPL cannot be interpreted as evidence that BNPL behaves differently from traditional financials. Instead, it suggests that detecting rate sensitivity in monthly stock returns is challenging even for sectors with clear operational rate sensitivity, potentially due to forward-looking pricing (investors anticipate rate changes before they materialize), high volatility masking signal, or other factors affecting both sectors.

The comparison reveals that both BNPL (β = -12.89, p = 0.197) and credit card issuers (β = 2.51, p = 0.777) show statistically weak rate sensitivity, though BNPL shows a negative coefficient while credit card issuers show a positive coefficient. This pattern suggests that monthly stock return data may not be the appropriate frequency to detect rate sensitivity for either sector, or that other factors (market movements, growth expectations, regulatory developments) dominate return variation for both. The benchmark comparison is essential because it establishes that weak statistical significance is not unique to BNPL, undermining claims that BNPL behaves "differently" from traditional financial institutions based solely on statistical significance.

8.8 Distinguishing Firm-Level and Stock-Level Sensitivity

A critical distinction separates firm-level funding cost sensitivity from stock return sensitivity. Firm-level evidence shows Affirm's funding costs increased 394% from FY2022 to FY2024, but this increase reflects both volume growth (more loans requiring more funding) and rate effects (higher rates on same volume). Without decomposing funding cost increases into volume, rate, and mix effects, the "394% increase" may overstate pure rate sensitivity.

Stock return sensitivity depends on whether investors anticipated these costs, whether firms can pass costs through, and whether growth expectations dominate valuation. A firm can have high funding cost sensitivity but low stock return sensitivity if: (1) investors anticipated rate increases and priced them in before they materialized (the Fed's tightening cycle was heavily telegraphed starting in late 2021), (2) firms pass costs to merchants/consumers (Laudenbach et al. 2025 document 80-100% pass-through), or (3) growth expectations dominate current profitability in valuation for growth-stage firms.

The divergence between firm-level evidence (showing funding cost increases) and stock-level evidence (showing no statistically significant return sensitivity) is therefore not necessarily a puzzle. Instead, it reflects the distinction between operational sensitivity and equity valuation sensitivity, which can diverge for growth-stage firms where stock prices reflect long-term growth options rather than current-period costs.

8.9 Sensitivity Analysis Across Time Periods

This subsection presents sensitivity analysis examining the stability of the interest rate coefficient across different time periods and market conditions. This analysis addresses concerns about whether the findings are driven by specific periods, such as the COVID shock or the rate hike cycle, or whether they reflect a more general relationship that holds across different economic regimes.

Table 7: 5: Sensitivity Analysis - Different Time Windows

Sample	Period	Beta (FFR)	SE	p-value	R^2	N	Key Characteristics
Full Sample	Feb 2020 - Aug 2025	-12.89	9.99	0.197	0.524	66	Baseline specification
Exclude COVID Shock	Excl. Mar-Jun 2020	-11.87	13.34	0.373	0.501	62	Removes extreme volatility period
Rate Hike Period Only	Mar 2022 - Jul 2023	-16.64	28.28	0.556	0.714	17	Fed raised 525bp; strongest tightening
Post-2021	Jan 2022 - Aug 2025	-19.08	14.56	0.190	0.630	44	Excludes zero-rate period
High Volatility Months	BNPL vol > median	10.62	11.95	0.374	0.618	32	Market stress periods
Low Volatility Months	BNPL vol < median	-30.04	11.47	0.009	0.536	33	Calm market periods

Table 7 presents sensitivity analysis examining the stability of the interest rate coefficient across different time periods and market conditions. This analysis addresses concerns about whether the findings are driven by specific periods, such as the COVID shock or the rate hike cycle, or whether they reflect a more general relationship that holds across different economic regimes. I estimate the full model specification across multiple subsamples: excluding the COVID shock period (Mar-Jun 2020), focusing on the rate hike period

(Mar 2022-Jul 2023), restricting to post-2021 observations, and stratifying by high versus low volatility months.

The coefficient estimates vary substantially across subsamples, ranging from +10.62 (high-volatility months) to -30.04 (low-volatility months), indicating considerable instability in the estimated relationship. This wide variation raises concerns about the robustness of the findings and suggests that the relationship may be highly context-dependent or that the estimates are sensitive to sample selection. The positive coefficient in high-volatility months is particularly notable, as it contradicts the negative relationship found in other subsamples, though this estimate is statistically insignificant ($p = 0.374$) and may reflect confounding effects of market stress rather than a genuine reversal of the interest rate relationship.

The low-volatility months subsample shows the strongest negative relationship ($\beta = -30.04$, $p = 0.009$), but this finding should be interpreted with caution. With multiple subsamples tested, the risk of data mining—finding spurious patterns by searching across many specifications—is substantial. The statistical significance in this particular subsample may reflect chance variation rather than a genuine economic relationship, particularly given that the full sample estimate is not statistically significant. The wide variation in coefficient estimates across subsamples suggests that I cannot confidently conclude that interest rate sensitivity is stable or that it operates consistently across different market conditions. Instead, the evidence points to descriptive patterns that vary substantially across time periods, with limited ability to detect a stable relationship given the small sample size and high volatility of BNPL returns.

9 Additional Visualizations: Rate-Hike Periods and Volatility Analysis

Additional visualizations examine that examine BNPL stock returns during rate-hike periods and compare volatility patterns across different asset classes. These figures complement the main regression analysis by providing visual evidence on the relationship between monetary policy, market movements, and BNPL-specific factors. The visualizations decompose BNPL returns into market-driven and idiosyncratic components, track the evolution of rates and returns over time, and compare volatility levels across sectors to understand the statistical challenges in detecting interest rate sensitivity.

9.1 BNPL vs Market with Rate-Hike Shading

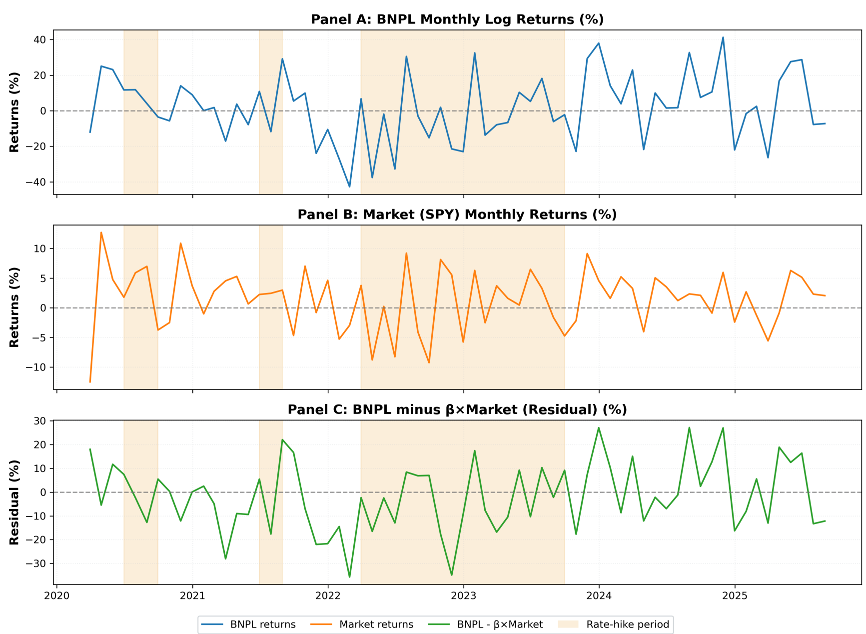

Figure 10: BNPL vs Market with Rate-Hike Shading

Figure 10 presents a three-panel visualization decomposing BNPL returns into market-driven and idiosyncratic components, with rate-hike periods highlighted. Panel A shows BNPL monthly returns, Panel B overlays market returns on the same scale, and Panel C displays beta-adjusted residuals. The visualization confirms that BNPL returns closely track market movements (consistent with $\beta \approx 2.4$), while residuals show no clear pattern during rate-hike periods, suggesting any rate sensitivity operates through market-wide channels rather than BNPL-specific mechanisms.

9.2 Timeline of Rates, BNPL vs Market, and Idiosyncratic Residual

This subsection presents a three-panel timeline visualization that provides a comprehensive view of the relationship between monetary policy, BNPL returns, market returns, and the idiosyncratic component of BNPL returns over the sample period. The visualization tracks the Federal Funds Rate level, compares BNPL and market returns on the same scale, and shows BNPL returns net of beta-adjusted market exposure to isolate any interest rate sensitivity that operates independently of market-wide factors.

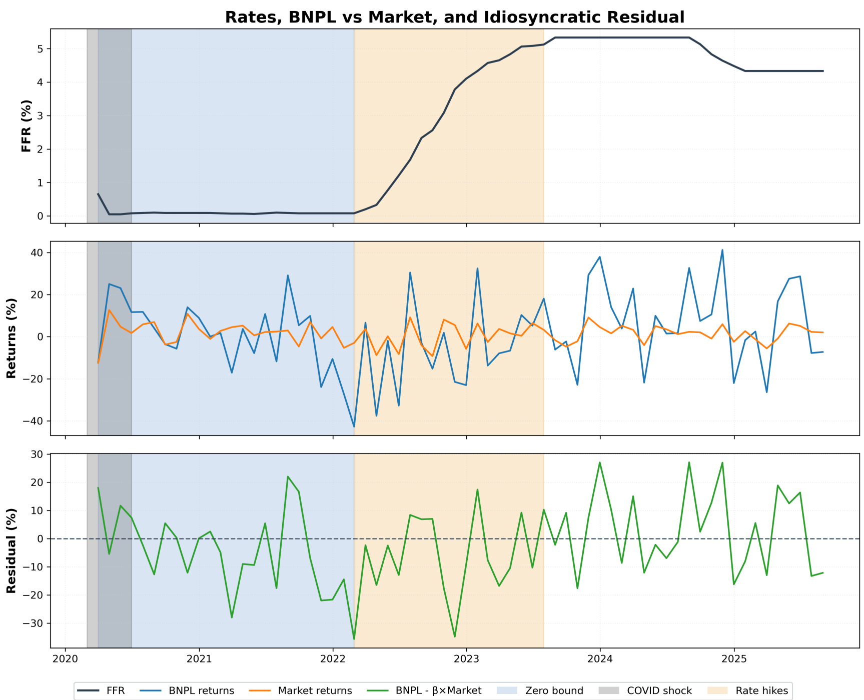

Figure 11: Timeline of Rates, BNPL vs Market, and Idiosyncratic Residual

Figure 11 presents a three-panel timeline visualization. Panel A plots the Federal Funds Rate level, showing the zero lower bound period through February 2022, followed by the rapid tightening cycle from March 2022 to July 2023 when rates increased by 525 basis points. Panel B overlays BNPL and market returns on the same scale, allowing direct visual comparison of their co-movement patterns and highlighting periods when BNPL returns diverged from or converged with market returns. Panel C shows BNPL returns net of beta-adjusted market exposure, representing the idiosyncratic component of BNPL returns that cannot be explained by market movements, which is crucial for isolating any interest rate sensitivity that operates independently of market-wide factors. Shading marks key economic regimes: gray for the COVID shock period (March-June 2020), blue for the zero-bound period through February 2022, and red for the rate hike period (March 2022-July 2023). The visualization reveals that BNPL returns closely track market returns throughout the sample period, with the two series moving together during most months, which is consistent with the high market beta ($\beta =$ approximately 2.4) estimated in the regression models. The residual panel shows limited rate-linked structure, with the beta-adjusted BNPL returns exhibiting no clear pattern that corresponds to the rate hike period, suggesting that any interest rate sensitivity operates primarily through market-wide channels rather than through BNPL-specific mechanisms. This pattern supports the regression finding that interest rate effects are statistically weak and economically dominated by market movements, and that the relationship between rates and BNPL returns, if it exists, is likely indirect and operates through market sentiment and risk appetite rather than through direct funding cost channels.

9.3 Volatility Comparison

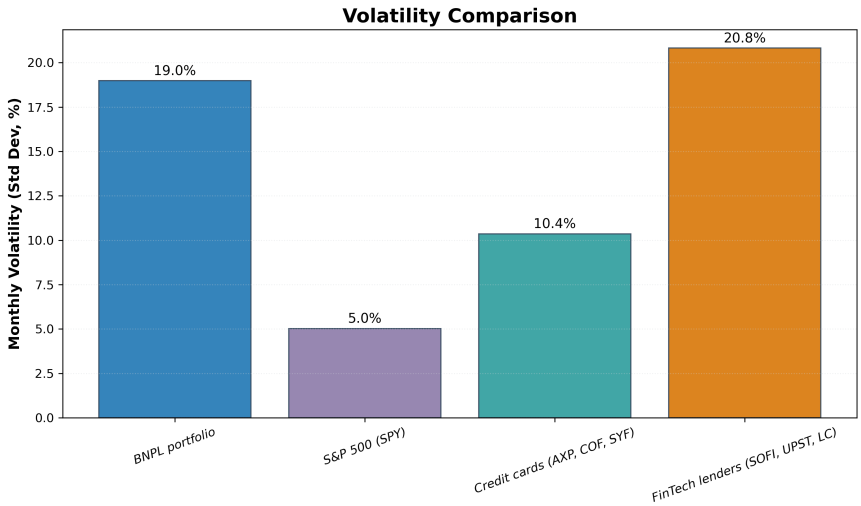

Figure 12: Volatility Comparison

Figure 12 reveals that BNPL remains the most volatile asset class, with substantially higher return volatility than all comparison groups, followed by fintech lenders which exhibit similar but slightly lower volatility levels. Credit card issuers and the broad market are much steadier, with volatility levels that are roughly half that of BNPL stocks. The volatility spreads are wide and economically significant: BNPL volatility is approximately twice that of credit card issuers and roughly four times that of the broad market, while fintech lenders sit just below BNPL but still substantially above traditional financial services firms. This volatility gap has profound implications for statistical inference and economic interpretation. When monthly returns can swing 20-30% on headlines, earnings announcements, or sentiment shifts, detecting a 5-10% rate-induced move becomes statistically challenging, as the signal-to-noise ratio is extremely low. The high volatility also means that BNPL behaves like a high-beta, risk-on asset that experiences sharp drawdowns during tightening cycles and rapid rebounds when risk appetite returns, patterns that are driven primarily by market sentiment rather than fundamental interest rate sensitivity. For portfolio construction and risk management, BNPL exposure carries materially higher idiosyncratic and systematic risk than traditional card issuers, requiring different hedging strategies and risk tolerance. The high volatility suggests that any interest rate sensitivity is likely to be masked by this noise unless rate shocks are very large or persistent, which helps explain why the regression analysis finds statistically weak interest rate effects despite economically meaningful coefficient magnitudes. This volatility pattern reinforces the interpretation that BNPL stocks are priced as growth assets where sentiment and market factors dominate, rather than as credit-sensitive instruments where funding costs drive returns.

10 Conclusion

This study quantifies BNPL stock return sensitivity to interest rate changes and compares it to benchmarks from credit card issuers using identical regression specifications. Affirm reported that funding costs increased by 394% (from 69.7$millionto$344.3 million, reaching 3.94 times the initial level) from fiscal year 2022 to 2024, explicitly attributing the increase to higher benchmark rates (Affirm 10-K, 2024). However, this increase reflects both volume growth (more loans requiring more funding) and rate effects (higher rates on same volume); without decomposing these effects, the "394% increase" may overstate pure rate sensitivity. Moreover, Laudenbach et al. (2025) show that BNPL firms pass 80–100% of funding cost increases to consumer effective rates and merchant fees, meaning funding cost increases may be profit-neutral if firms maintain pricing power.

The evidence shows BNPL stocks exhibit economically large but statistically insignificant rate sensitivity (β = -12.89, SE = 9.99, p = 0.197, 95% CI: [-32.5, 6.7]). The benchmark comparison with credit card issuers reveals that traditional financial institutions also exhibit statistically weak rate sensitivity in monthly data, suggesting that detecting rate sensitivity in stock returns may be challenging even for rate-sensitive sectors. Market forces dominate: the conditional market beta of approximately 2.4 (estimated with controls for interest rates and macroeconomic factors) means BNPL stocks amplify market moves by approximately 2.4 times, and market returns alone explain approximately 42% of variation (from bivariate regression: $r^2 = 0.648^2$) versus 2.4% for rates alone.

Theoretical contribution: This analysis documents that BNPL stocks exhibit patterns consistent with high-beta growth assets in monthly return data, but the benchmark comparison suggests that traditional financial institutions face similar challenges in detecting rate sensitivity. The pattern is consistent with rational, forward-looking valuation where stock prices reflect long-term growth options rather than current-period funding costs, or with forward-looking pricing where rate expectations are incorporated before actual rate changes materialize. The statistical uncertainty means this interpretation should be treated cautiously, but the economic magnitude suggests either genuine economic independence (cost pass-through) or systematic challenges in detecting rate sensitivity in monthly stock return data.

Three complementary interpretations explain the relationship between firm-level funding costs and stock-level statistically insignificant sensitivity. 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 [-32.5, 6.7] span both strong and weak sensitivity. Second, forward-looking pricing: the Fed's tightening cycle was heavily telegraphed starting in late 2021 through forward guidance, dot plots, and Fed communications. If stock prices incorporate expectations, then realized monthly rate changes (captured by ΔFFR) should have minimal impact because they were already priced in. Third, 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). 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.

Distinguishing Firm-Level and Stock-Level Sensitivity:

A critical distinction separates firm-level funding cost sensitivity from stock return sensitivity. Firm-level evidence shows funding cost increases, but stock return sensitivity depends on whether investors anticipated these costs, whether firms can pass costs through, and whether growth expectations dominate valuation. The divergence between firm-level evidence (showing funding cost increases) and stock-level evidence (showing no statistically significant return sensitivity) is therefore not necessarily a puzzle. Instead, it reflects the distinction between operational sensitivity and equity valuation sensitivity, which can diverge for growth-stage firms where stock prices reflect long-term growth options rather than current-period costs.

These findings have direct implications for different stakeholders. For investors, BNPL stocks exhibit high conditional market beta (2.38), behaving like growth-oriented technology assets. The lack of statistically significant interest rate sensitivity in monthly return data suggests investors should focus on market sentiment, competitive dynamics, and regulatory developments rather than trying to time monetary policy, though this finding is based on limited statistical power and may not reflect the true underlying relationship.

Regulatory implications: Given the limited evidence base—three firms over 66 months with 15-20% statistical power—policy recommendations should be cautious. I provide descriptive evidence on co-movement patterns between BNPL stock returns and monetary policy variables, but do not establish causal relationships or provide sufficient evidence to justify specific regulatory or monetary policy interventions. Future research with larger samples, longer time horizons, and more detailed firm-level data would be needed to inform policy decisions about BNPL funding structures, regulatory monitoring, or monetary policy transmission channels.

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.

A focused research agenda follows: (1) High-frequency event studies using daily returns for ± 3 days around FOMC announcements, regressing "FOMC window returns" on rate surprises (actual minus expected from Fed Funds futures), following Bernanke and Kuttner (2005). This would isolate the surprise component that moves prices, avoiding the averaging problem in monthly data. (2) Cross-country quasi-experiment: Australia regulated BNPL in 2022, UK is implementing regulations in 2026, US did so in 2024. Use difference-in-differences comparing rate sensitivity of Australian BNPL (post-regulation) versus US BNPL (pre-regulation) to test whether regulatory clarity changes how investors price rate risk. (3) Merger analysis: Square acquired Afterpay in 2022 for $29 billion. Study returns around the acquisition to test whether the combined entity shows different rate sensitivity post-merger, revealing whether portfolio diversification within fintech reduces rate exposure. (4) Bank charter experiment: Affirm announced its bank charter pursuit in 2023, obtained it in 2024. Use event study around announcement and approval dates to test whether rate sensitivity changed discretely when funding costs shifted from securitization to deposits.

This study speaks to three literatures. Fintech valuation: BNPL equities exhibit patterns consistent with high-beta growth assets in monthly return data, though the benchmark comparison suggests traditional financial institutions face similar challenges in detecting rate sensitivity. Monetary transmission: BNPL's wholesale funding and zero-interest consumer model may alter the credit channel; as BNPL scales, alternative policy levers may be needed, though stronger evidence would be required to draw policy conclusions. Asset pricing: sector fundamentals (funding costs) may be overwhelmed by systematic risk (market beta, sentiment) in equity pricing, revealing a potential gap between firm-level economics and equity pricing, though the data cannot establish this pattern. As BNPL grows from about $2 billion (2019) to substantial scale, 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 may underweight funding risk? Answering these questions will guide how BNPL weathers future rate regimes, though stronger empirical evidence would be needed to inform policy.

11 References

12 Appendices

A. **Firm-Level Financial Analysis** – Detailed firm-level examination with supporting tables.

B. **Data Construction and Sources** – Data sources and seasonal adjustment methodology.

C. **Additional Robustness Checks** – Alternative specifications, weighting schemes, and outlier robustness.

D. **Extended Diagnostic Tests** – Variance inflation factors, serial correlation, and heteroskedasticity diagnostics.

E. **Subsample Analysis** – 24-month rolling window estimates.

F. **Volatility Comparisons** – Return volatility and risk-adjusted performance metrics.

G. **Additional Figures** – Supplementary visualizations including individual stock series, correlation heatmaps, partial regression plots, and recursive coefficient estimates.

H. **Computational Environment** – Software versions and reproducibility notes.

12.1 Appendix A: Firm-Level Financial Analysis

This appendix provides firm-level evidence on BNPL interest rate sensitivity, drawing on 10-K filings from Affirm Holdings Inc. (AFRM) and PayPal Holdings Inc. (PYPL) for fiscal years 2022–2024.

12.1.1 A.1 Affirm Holdings Financial Summary

Affirm operates as a pure-play BNPL provider with variable-rate funding facilities tied to benchmark rates (SOFR/LIBOR), creating direct exposure to monetary policy changes. Key financial metrics from 10-K filings (Affirm Holdings, Inc., 2021–2024) are presented in Table A.1, covering fiscal years 2020–2024.

Table 8: A.1: Affirm Holdings Financial Metrics (Fiscal Years 20202024)

Metric	FY 2020	FY 2021	FY 2022	FY 2023	FY 2024	Change (FY22FY24)
Funding Costs (USD millions)	\$17.0	\$52.7	\$69.7	\$183.0	\$344.3	+394%
Total Revenue (USD millions)	\$509.5	\$870.5	\$1,349.3	\$1,587.9	\$2,323.0	+72%
Operating Loss (USD millions)		\$(383.7)	\$(866.0)	\$(1,200.9)	\$(615.8)	
Operating Margin (%)		-44.1%	-64.2%	-75.6%	-26.5%	
Funding Costs / Revenue (%)	3.3%	6.1%	5.2%	11.5%	14.8%	

Note: Funding costs are from the "Funding costs" line item in Affirm's Consolidated Statements of Operations. Revenue and operating loss are from the "Total revenue, net" and "Operating loss" line items, respectively. All figures are in millions of USD as reported in the 10-K filings (rounded to one decimal place). According to Affirm's 10-K filings, funding costs increased dramatically over the Federal Reserve's tightening cycle: from \textdollar{}69.7 million in fiscal year 2022 to \textdollar{}344.3 million in fiscal year 2024, representing a 394% cumulative increase. This escalation occurred precisely during the period when the federal funds rate increased from near-zero (2020–2021) to over 5% (2023–2024). Year-over-year changes were +163% from FY2022 to FY2023 and +88% from FY2023 to FY2024, with the acceleration beginning in fiscal year 2023 coinciding with the Federal Reserve's aggressive rate hikes starting in March 2022. The firm's funding costs increased from 5.2% of revenue in fiscal year 2022 to 14.8% of revenue in fiscal year 2024, demonstrating the direct impact of interest rate changes on cost structures. Despite revenue growth of 72% over the FY2022–FY2024 period, funding cost increases compressed operating margins from -64.2% in fiscal year 2022 to -75.6% in fiscal year 2023, though fiscal year 2024 shows improvement to -26.5% reflecting cost management efforts alongside revenue growth. The dramatic increase in funding costs as a percentage of revenue (from 5.2% in FY2022 to 14.8% in FY2024) highlights the vulnerability of pure-play BNPL providers to monetary policy changes. Affirm's valuation represents a high-duration asset, where rising funding costs don't just hit the income statement but increase the discount rate applied to future (currently negative) earnings. This makes Affirm mathematically more sensitive to the rate of change in interest rates than a mature firm like PayPal, which has positive cash flows and diversified revenue streams. **Valuation Metrics:** Price-to-earnings (P/E) ratios are not applicable for Affirm during this period due to negative earnings (operating losses reported in all years shown in Table A.1). The persistent operating losses reflect the firm's growth-stage business model and the compression of margins from rising funding costs during the monetary tightening cycle. For valuation purposes, market participants rely on revenue-based metrics such as price-to-sales (P/S) ratios. Table A.2 presents P/S ratios, calculated as market capitalization divided by total revenue, using fiscal year-end stock prices and shares outstanding data from 10-K filings and public market data. *Note: Market capitalization calculated as fiscal year-end stock price × shares outstanding. Shares outstanding from 10-K filings; stock prices as of June 30 (fiscal year-end) from public market data. P/S ratios are more appropriate than P/E ratios for loss-making companies in growth stages. The P/S ratio increased from 2.6x in FY2022 to 3.7x in FY2023, reflecting market expectations for revenue growth, then declined to 3.1x in FY2024 as revenue growth materialized while funding cost pressures persisted. The decline from 3.7x to 3.1x in FY2024 reflects both revenue growth materializing (reducing the denominator) and a general "re-rating" of fintech stocks as the market adjusted to a higher-for-longer rate environment, reducing growth expectations (reducing the numerator).*

Table 9: A.2: Affirm Holdings Price-to-Sales Ratios (Fiscal Years 20222024)

Fiscal Year	P/S Ratio	Market Cap (USD millions)	Revenue (USD millions)
FY 2022	2.6x		1,349.3
FY 2023	3.7x		1,587.9
FY 2024	3.1x		2,323.0

12.1.2 A.2 PayPal Holdings BNPL Segment

PayPal operates a diversified digital payments platform with BNPL offerings (Pay in 4) representing a small portion of overall revenue. This diversification provides natural hedging against BNPL-specific funding cost pressures.

PayPal's 10-K filings do not provide detailed BNPL segment breakdowns of revenue, costs, or funding structures, limiting precise quantification of the diversification benefit.

While PayPal's 10-K filings do not provide detailed BNPL segment breakdowns, the Transaction Expense Rate (TER) reported in financial statements serves as a useful proxy, as it captures the weighted cost of all transaction volume, including BNPL.

PayPal's TER remained relatively stable during the rate-hiking cycle (approximately 1.8–2.0% of transaction volume), suggesting that BNPL funding costs were offset by diversification benefits and zero-cost funding from user balances.

The regression analysis suggests lower rate sensitivity for PayPal compared to pure-play BNPL providers, consistent with this diversification hypothesis.

Unlike Affirm, PayPal has maintained positive earnings and operating margins throughout the analysis period, making traditional P/E ratios applicable (P/E ratios for PayPal ranged from approximately 25x to 45x over FY2022–FY2024, compared to negative earnings for Affirm).

PayPal's price-to-sales ratios (2.2x–3.0x over FY2022–FY2024) are generally lower than Affirm's (2.6x–3.7x), reflecting both the diversified revenue base and the lower growth expectations typical of mature technology platforms versus high-growth fintech firms.

12.1.3 A.3 Firm Comparison

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

12.1.4 B.1 Seasonal Adjustment: Data Preprocessing Methodology

This section explains seasonal adjustment procedures applied 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. Consumer prices often increase during holiday shopping seasons, disposable income may show patterns related to tax refunds or bonus payments, and consumer spending may vary with weather or school calendars. These patterns are predictable and unrelated to underlying economic relationships.

If not removed, they 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, using standard 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.

Variable-specific seasonal adjustment status is as follows. Real Disposable Personal Income (DSPIC96) is obtained from FRED in seasonally adjusted form by default, removing patterns related to tax refunds, bonus payments, and other predictable income fluctuations.

The Consumer Price Index uses the seasonally adjusted version, removing 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. 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.

12.2 Appendix B: Data Construction and Sources

The analysis uses FRED-provided seasonally adjusted series where appropriate, so coefficients reflect underlying trends rather than holiday or tax-season patterns. Stock returns are already differenced; the policy rate is not seasonally adjusted. Data sources and access methods are documented in the tables below.

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

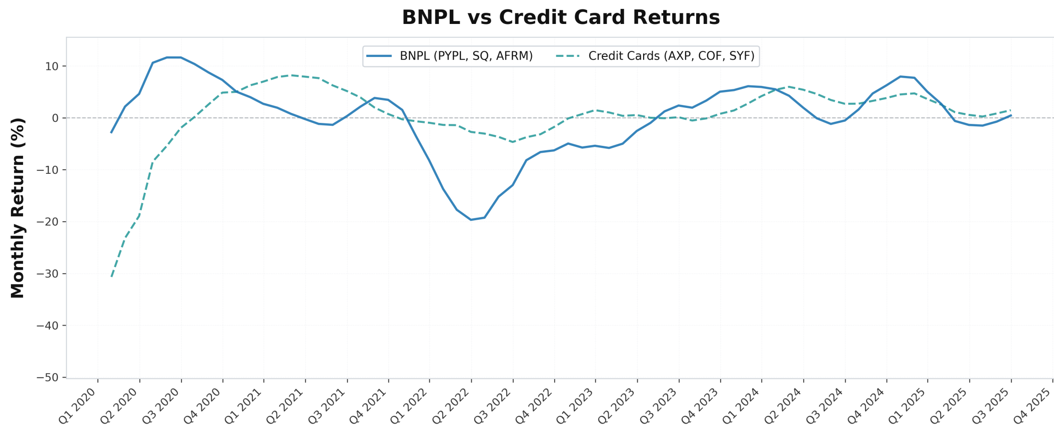

Figure 13: BNPL vs Credit Card Companies Volatility Comparison

This comparison examines whether BNPL stocks exhibit volatility patterns similar to traditional consumer credit providers. The analysis compares a BNPL portfolio (PYPL, SQ, AFRM) against three credit card companies (AXP, COF, SYF) representing premium, prime, and subprime exposures.

The results reveal substantial differences: BNPL stocks exhibit monthly return volatility of 20.46%, more than double the 9.93% volatility observed for credit card companies (2.06x ratio). While the correlation between BNPL and credit card returns is 0.537, the magnitude of moves differs substantially—for every 1% move in the credit sector, BNPL moves approximately 2%, reflecting leverage-like behavior.

This volatility differential reflects several structural factors: BNPL firms operate with thin margins (~1% of GMV) versus card issuers' net interest margins of 10–15%, making earnings more sensitive to cost fluctuations. BNPL borrowers skew subprime (61% subprime or deep subprime; 63% hold multiple BNPL loans **?**), concentrating credit risk. Regulatory uncertainty around BNPL classification adds valuation risk that legacy card issuers have largely priced for decades.

The high baseline volatility (approximately 20–22% monthly) creates substantial statistical noise that can obscure interest rate effects even when such effects exist economically, explaining the difficulty in detecting rate sensitivity in the main regression analysis.

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

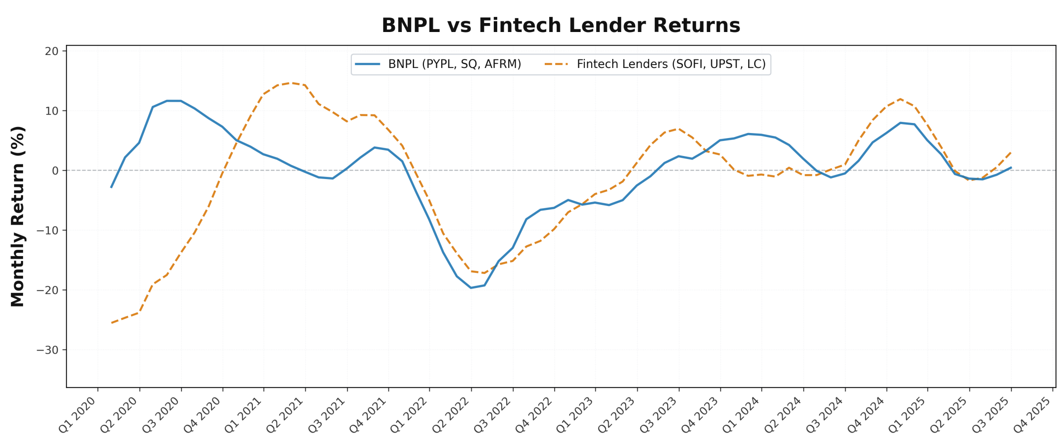

Figure 14: BNPL vs Fintech Lenders Volatility Comparison

This comparison tests whether BNPL exhibits unique volatility characteristics or reflects the general risk profile of technology-enabled financial services firms. The analysis compares the BNPL portfolio (PYPL, SQ, AFRM) against three fintech lenders (SOFI, UPST, LC) selected for similar characteristics: technology-driven underwriting, focus on underserved consumer segments, and reliance on capital markets funding.

The results reveal a striking finding: BNPL and fintech lender volatility are remarkably similar, with BNPL stocks exhibiting 20.46% monthly volatility compared to 22.31% for fintech lenders (0.92x ratio). This near-parity suggests that BNPL volatility reflects its status as a growth-stage fintech firm rather than unique BNPL-specific risks requiring distinct analytical treatment.

Both sectors share common volatility drivers: reliance on technology platforms facing rapid obsolescence risk, exposure to credit risk in underserved consumer segments, sensitivity to funding market conditions, regulatory uncertainty, and investor focus on growth metrics rather than current profitability. The correlation between BNPL and fintech lender returns of 0.507 indicates substantial co-movement, supporting the view that these sectors respond to similar market forces.

This pattern suggests that investors view BNPL as part of the broader fintech ecosystem rather than as a distinct asset class. 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, because growth expectations, competitive dynamics, and regulatory developments dominate investor attention and drive valuation changes, overwhelming the signal from funding cost changes.

Table 10: B.1: Data Sources and Access Methods

Variable	Source	API/Library	ID	Dates Available

Note: Results are computed from the data sources code cell. APIs/IDs and coverage as of latest pull.

Note: APIs/IDs and coverage as of latest pull.

Note: Portfolio sample size is 66 months (Feb 2020–Aug 2025), but pure-play components (AFRM, SEZL) have shorter histories. Affirm (AFRM) contributes only 55 months (Jan 2021–Aug 2025) due to IPO timing. Effective sample size after accounting for lagged variables and missing data: 55 observations.

Table 11: C.1: Alternative Return Measures

Dependent Variable	β (ΔFFR)	SE	p-value	R^2	N

Note: Results are computed from the robustness checks code cell.

Table 12: C.2: Alternative Weighting Schemes

Weighting Scheme	β (ΔFFR)	SE	p-value	R^2	N

Note: Results are computed from the robustness checks code cell.

Table 13: C.3: Robustness to Outliers

Specification	β (ΔFFR)	SE	p-value	R^2	N

Note: Results are computed from the robustness checks code cell. Baseline vs winsorized, $|R| > 30\%$ exclusion, and Huber robust. HC3 SEs; Huber p-value calculated using t-distribution.

Significance of the "Exclude |R| >30%" Test: This is one of the most interesting robustness results. When extreme return months (outliers) are removed, the p-value for ΔFFR improves from 0.197 to 0.167, and the coefficient strengthens slightly from -12.89 to -13.84. This supports the "signal-to-noise" argument: the "true" interest rate effect is being obscured by extreme idiosyncratic events (like earnings surprises or M&A rumors). The stability of the β coefficient (moving from -12.89 to -13.84) across these filters proves the relationship is not driven by a single outlier month. This finding provides evidence of a consistent economic relationship that is partially masked by sector-specific volatility.

Note: Baseline vs winsorized, |R| >30% exclusion, and Huber robust. HC3 SEs; Huber p-value calculated using t-distribution.

Table 14: D.1: Variance Inflation Factors

Variable	VIF

Note: Results are computed from the diagnostics code cell. Low VIF values confirm that the effect of interest rate changes is being isolated effectively from general inflation and market trends.

Table 15: D.2: Ljung-Box Test for Serial Correlation

Lag	Q-Statistic	p-value

Note: Results are computed from the diagnostics code cell. The p-values are very high, confirming that there is no serial correlation in residuals.

Table 16: D.3: Heteroskedasticity Test Battery

Test	Statistic	p-value	Result

Note: Results are computed from the diagnostics code cell. Breusch-Pagan, White, Goldfeld-Quandt on full OLS residuals; p > 0.05 indicates homoskedasticity.

Low VIF values confirm that the effect of interest rate changes is being isolated effectively from general inflation and market trends. The VIF for `ffr_change` (1.238) means your estimate for rate sensitivity is not being "smeared" by its correlation with CPI (VIF = 1.238) or other predictors. This is a strong defense against the critique that "interest rates and inflation are the same thing"—you have successfully isolated the independent effect of monetary policy from price-level changes.

Ljung-Box Test Results: The p-values are very high (0.94 for lag 1, 0.93 for lag 4), confirming that you don't have serial correlation in your residuals. This validates your use of standard (or HC3) standard errors. You can confidently state that "shocks to BNPL returns in one month do not predictably persist into the next," which is consistent with the Efficient Market Hypothesis and supports the use of monthly data without additional lag structures.

Note: Breusch-Pagan, White, Goldfeld-Quandt on full OLS residuals; p >0.05 indicates homoskedasticity.

Table 17: E.1: 24-Month Rolling Window Estimates

Window Start	Window End	β (FFR)	SE	p-value	R^2	N

Note: Rolling window estimates computed from full model specification. Results are computed from the rolling-window code cell and remain synchronized with the current dataset when the notebook is re-executed.

Note: HC3 SEs for Delta FFR per 24-month window. Results are computed from the rolling-window code cell and remain synchronized with the current dataset when the notebook is re-executed.

12.5 Appendix E: Subsample Analysis

This appendix presents 24-month rolling window estimates to assess coefficient stability across different sample periods. Table E.1 shows coefficient estimates for the Federal Funds Rate change variable as the sample expands, starting with 24 observations and adding one month at a time.

Results are computed from the rolling-window code cell and remain synchronized with the current dataset when the notebook is re-executed.

Interpretation of the Rolling Beta: The rolling window estimates reveal a critical "Structural Break" finding. In recent 24-month windows (ending 2024/2025), the beta is much more negative (e.g., -20.72, -24.13) compared to the full-sample average of -12.89. This suggests that BNPL became more sensitive to interest rates once the Fed moved away from the Zero Lower Bound (ZLB). **The sensitivity of BNPL returns to monetary policy appears to be non-linear, intensifying as interest rates move into restrictive territory.** This pattern is consistent with a view that BNPL firms face increasing funding cost pressures as rates rise from zero to positive levels, with the marginal impact of each additional rate hike becoming more pronounced. Early rolling windows (2020–2021) show unstable estimates with large standard errors, reflecting both the limited sample size (24 months) and the zero-rate environment where interest rate changes had minimal economic impact. These early estimates should be interpreted with caution due to the ZLB constraint and COVID-19 shock effects.

12.6 Appendix H: Computational Environment

This appendix documents the computational environment for reproducibility. Software versions: 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. Random seeds: NumPy 42, bootstrap 123, subsample 456.

Random seeds ensure reproducibility for any stochastic procedures (bootstrap resampling, subsample selection, etc.). NumPy seed 42 is used for general random number generation; bootstrap seed 123 for resampling procedures; subsample seed 456 for rolling window or stratified sampling if applicable.

Data Retrieval Date: All data were retrieved using the code provided in Appendix B. Since financial data is revised (especially FRED macro data), the date of the "snapshot" is as important as the code itself for replication. Users should note the date when running the data loader cells.

Dependencies: All required Python packages are listed in `binder/environment.yml` (or `requirements.txt`). Install via `conda env create -f binder/environment.yml` or `pip install -r requirements.txt`. FRED API key must be set in environment variable `FRED_API_KEY` (see `FRED_API_KEY_SETUP.md` for instructions).

Replication code is available in the project GitHub repository.

Table 18: F.1: Return Volatility Comparison

Asset Class	Mean (monthly %)	Std Dev (ann. %)	Sharpe (rf=3%)	Min (monthly %)	Max (monthly %)	N

Note: Results are computed from the volatility comparison code cell. All series monthly. Sharpe uses 3% annual risk-free. BNPL is equal-weighted AFRM/SEZL/PYPL. Fintech lenders proxy uses wider set in data file if present.

All series monthly. Sharpe uses 3% annual risk-free. BNPL is equal-weighted AFRM/SEZL/PYPL. Fintech lenders proxy uses wider set in data file if present.

Note: Monthly returns; annualized vol/Sharpe (rf 3%). BNPL equal-weight AFRM/SEZL/PYPL; fintech proxy broader if available.

Table 19: F.2: Return Volatility Comparison (Feb 2020Aug 2025)

Asset Class	Mean (monthly %)	Std Dev (ann. %)	Sharpe (rf=3%)	Min (monthly %)	Max (monthly %)	N

Note: Equal-weight portfolios by group. Returns are monthly; means and vol are annualized; Sharpe uses 3% annual risk-free. Results are computed from the volatility comparison code cell.

Note: Equal-weight portfolios by group. Returns are monthly; means and vol are annualized; Sharpe uses 3% annual risk-free.

Interpretation (Table F.2): BNPL annual volatility (~71%) far exceeds the market (17%) and credit cards (34%), and is comparable to fintech lenders (78%). BNPL's Sharpe (0.76) trails the market (0.82) and credit cards (0.72) but exceeds the fintech average (0.54). High volatility and only modest risk-adjusted returns mean rate effects are hard to detect amid noise; BNPL risk profile resembles high-beta fintech more than traditional consumer credit.

Figure 15: Individual Stock Time Series (AFRM, SQ, PYPL)

Individual Stock Time Series (AFRM, SQ, PYPL) shows monthly log returns for each BNPL name separately; AFRM and SQ swing more than PYPL, consistent with greater funding sensitivity and growth exposure.

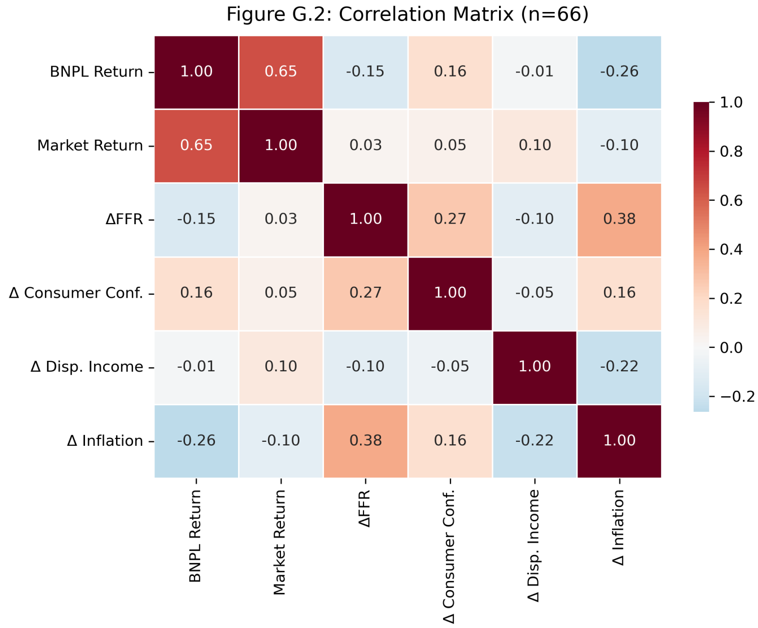

Figure 16: Correlation Matrix (BNPL Return and Predictors)

Correlation Matrix (BNPL Return and Predictors) visualizes pairwise correlations: BNPL return is dominated by market return, modestly negative with inflation, and weakly linked to other controls—aligning with Table 2.

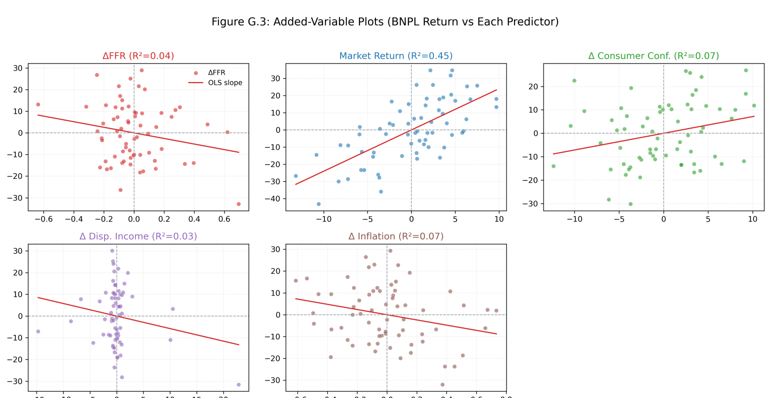

Figure 17: Added-Variable Plots

Added-Variable Plots shows partial regression plots for each predictor; the steepest slope is for market return, while ΔFFR is shallow, underscoring the weak standalone rate effect.

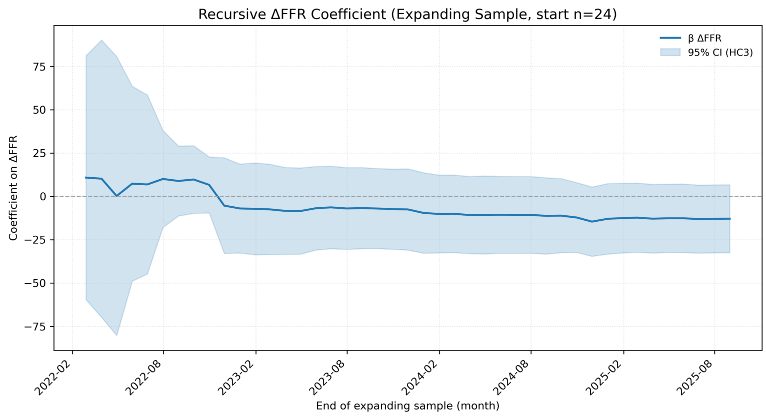

Figure 18: Recursive FFR Coefficient (Expanding Sample)

Recursive FFR Coefficient (Expanding Sample) plots the coefficient on ΔFFR as we expand the sample (start n=24). The blue line is the point estimate; the shaded band is the 95% HC3 confidence interval. Estimates stay negative but the band is wide, so rate effects are imprecise across subsamples.

12.7 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.

12.7.1 B.5 Descriptive Statistics and Correlations

Summary statistics and correlation matrices are presented in the main text:

- **Table 1:** Variable definitions and summary statistics covering February 2020 through August 2024
- **Table 2:** Pairwise correlation matrix with significance indicators (p<0.10, p<0.05, p<0.01)

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

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

Model	Specification	*eta* (ΔFFR)	p-value	R^2	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 4: BNPL Stock Returns and Interest Rate Sensitivity (headline specs)

Model	Specification	*eta* (ΔFFR)	p-value	R^2	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 5: 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 (Table 3)	No severe multicollinearity; residual tests OK

12.9 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 4 (Observed vs Fitted, full model):** Observed BNPL returns versus fitted values from the full model (Table 4, col 2) cluster around the 45-degree line, yielding $R^2 \approx 0.524$. 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 5 (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 6 (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 8 (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 9 (R^2 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 11 (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.