

# The Networked Reallocation: Social Connectedness and Deposit Sorting During the 2023 Banking Panic

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## Abstract

When Silicon Valley Bank collapsed in March 2023, did private social networks spread the panic—or help depositors make better decisions? Using the Facebook Social Connectedness Index to measure county-level exposure to SVB’s geographic footprint, I decompose the deposit response into two channels. Total deposits (including failed banks) fell more in socially connected counties, replicating the “social contagion” pattern. But excluding deposits at SVB, Signature Bank, and First Republic reveals the opposite: non-failed banks in connected counties *gained* deposits. A one-standard-deviation increase in network exposure predicts 0.49 percentage points higher deposit growth at surviving institutions ( $p < 0.001$ ). Five pre-period placebos and a JPMorgan non-failing-bank placebo yield null effects. The results suggest social ties facilitated informed deposit reallocation away from vulnerable banks rather than indiscriminate panic—a *networked reallocation* rather than a networked run.

**JEL Codes:** G01, G21, G28, L14

**Keywords:** bank runs, social networks, financial contagion, deposit reallocation, SVB

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# 1. Introduction

The collapse of Silicon Valley Bank on March 10, 2023—the largest bank failure since 2008—raised a fundamental question about digital-age financial crises: do social networks spread panic, or do they help people make better decisions? The emerging literature has emphasized the first channel. [Cookson et al. \(2025\)](#) show that Twitter activity predicted deposit outflows during the SVB panic, suggesting that social media amplified the run. But this finding conflates two effects: social networks could transmit *fear* (causing indiscriminate runs on all banks) or *information* (helping depositors distinguish failing from healthy institutions). The distinction matters profoundly for policy: if networks spread panic, regulators should consider communication interventions; if they spread information, networks are self-correcting.

This paper tests the distinction by decomposing the deposit response to the 2023 banking panic. I construct a county-level measure of social connectedness to Silicon Valley using the Facebook Social Connectedness Index (SCI), which captures the probability that two users in different counties are Facebook friends ([Bailey et al., 2018](#)). SVB operated just 17 branches across 9 California counties, with 51.6% of its deposit market share in Santa Clara County alone, providing a clean geographic epicenter for a shift-share design. The key empirical move is to separate deposits at failed institutions (SVB, Signature Bank, First Republic) from deposits at surviving banks.

The decomposition reveals a striking reversal. When total county deposits are used as the outcome—as previous studies have done—social connectedness to SVB predicts larger deposit declines, consistent with the contagion narrative. But when I exclude deposits at the three failed banks and examine only surviving institutions, the sign flips: a one-standard-deviation increase in network exposure predicts 0.49 percentage points *higher* deposit growth at non-failed banks ( $p < 0.001$ ). Five pre-period placebos (2017–2022) show null effects. A non-failing-bank placebo using JPMorgan Chase’s 4,818-branch footprint yields a precisely estimated zero. The result survives dropping California entirely and restricting to counties more than 500 kilometers from Santa Clara County.

The positive coefficient on non-failed bank deposits is consistent with a *networked reallocation* mechanism: depositors in socially connected counties received private information about SVB’s specific vulnerabilities and moved their money to safer local institutions rather than panicking about the banking system as a whole. This interpretation aligns with the finding that the effect is concentrated in high-deposit counties, where depositors have the resources and sophistication to distinguish between failing and healthy banks. The Diamond-Dybvig model ([Diamond and Dybvig, 1983](#)) predicts that better information reduces the probability of inefficient runs; private social networks may provide exactly this kind of informed

coordination.

This paper contributes to the debate on social networks and financial stability in three ways. First, it shows that the apparent “social contagion” pattern in aggregate deposits is mechanical—it reflects direct losses at failed institutions, not panic spreading to other banks. This challenges the narrative that social networks destabilize the financial system (Cookson et al., 2025; Goldstein and Pauzner, 2005). Second, it provides the first evidence that real social ties (as opposed to social media broadcasts) facilitated efficient deposit reallocation during the 2023 panic, complementing Iyer and Puri (2012)’s finding that bank-depositor relationships shape run behavior. Third, it demonstrates the importance of decomposing aggregate outcomes in crisis research: without separating failed from surviving institutions, the same data supports opposite conclusions about the role of social networks.

This paper also relates to the broader literature on information and financial crises (Bernanke, 1983; Allen and Gale, 2000; Acharya and Yorulmazer, 2008; He and Manela, 2016), the growing evidence on social networks and economic behavior (Bailey et al., 2018, 2019; Kuchler et al., 2022), and work on the 2023 banking panic specifically (Jiang et al., 2024; Granja, 2023; Choi et al., 2023). The finding that social ties promote reallocation rather than panic is consistent with Kiss et al. (2014)’s laboratory evidence that social network information can prevent bank runs, and extends Flynn and Wang (2025)’s demonstration that SCI predicts precautionary savings behavior in response to natural disasters.

## 2. Institutional Background

**The SVB Failure and the March 2023 Panic.** Silicon Valley Bank (SVB), headquartered in Santa Clara, California, was the 16th-largest U.S. bank by assets (\$209 billion) at failure. Approximately 94% of its deposits exceeded the FDIC’s \$250,000 insurance limit (Federal Deposit Insurance Corporation, 2023). Rising interest rates inflicted mark-to-market losses on SVB’s held-to-maturity securities, and when the bank disclosed a \$1.8 billion loss on March 8, depositors withdrew \$42 billion in 24 hours—the fastest bank run in history (Barr, 2023). Signature Bank was seized on March 12, and First Republic Bank lost \$70 billion in deposits before its seizure on May 1. The FDIC invoked its systemic risk exception, guaranteeing all deposits at SVB and Signature.

**SVB’s Geographic Concentration.** SVB’s branch network was unusually concentrated: 17 branches across 9 California counties, with the majority in Santa Clara County (51.6% of SVB’s deposit market share). This concentration provides the key identification advantage: cross-county variation in social connectedness to SVB’s footprint generates exposure variation

that is distinct from geographic proximity to Silicon Valley more broadly.

**The Social Connectedness Index.** The Facebook SCI measures the relative probability that two users in different locations are Facebook friends (Bailey et al., 2018). Unlike social media activity measures, SCI captures *real social relationships*—friendship, family ties, professional connections—that operate through private channels. The January 2026 release covers all U.S. county pairs (10.3 million observations). SCI has been validated as a predictor of trade flows, migration, house prices, and economic sentiment (Bailey et al., 2019; Kuchler et al., 2022).

### 3. Data

I combine four data sources to construct the county-level analysis dataset.

**FDIC Summary of Deposits.** The SOD provides branch-level deposit data for every FDIC-insured institution as of June 30 each year. I collect data for 2017–2023 (588,031 branch-year observations). The key outcome is the log change in county deposits from June 2022 to June 2023, computed *after excluding deposits at SVB (CERT 24735), Signature Bank (CERT 57053), and First Republic Bank (CERT 59017)*. This exclusion ensures the outcome captures contagion to surviving banks rather than direct losses at failed institutions. Five pre-period changes (2017–2022) serve as placebos.

**Social Connectedness Index.** I download the U.S. county-pair SCI (10.3 million pairs) and identify SVB’s 17 branches across 9 counties in the June 2022 SOD. Each county’s NetworkExposure equals the SCI-weighted SVB deposit market share across connected counties.

**County Controls.** BEA personal income and population (2022), Census QWI NAICS 51 (Information sector) employment share as a proxy for tech concentration, and Haversine distances from county centroids to Santa Clara County.

**Sample.** The analysis sample contains 3,164 counties across 50 states and territories, retaining 3,025 observations in the preferred specification with full controls and state fixed effects.

**Table 1:** Summary Statistics

Variable	Mean	SD	P25	P75
$\Delta$ Log Deposits (2022–2023)	-0.0245	0.1342	-0.0598	0.0159
Network Exposure (raw)	1,796	8,538	559.991	1,302
Network Exposure (std.)	-0.0000	1.000	-0.1448	-0.0579
Distance to SV (km)	2,829	1,026	2,237	3,491
Tech Employment Share	0.0097	0.0122	0.0036	0.0123
Deposits 2022 (\$000s)	5,536,726	41,619,529	258,858	1,590,258
Population (2022)	107,772	337,955	11,312	69,953

*N* = 3,164 counties across 55 states.

## 4. Empirical Strategy

For each county  $c$ , I construct:

$$\text{NetworkExposure}_c = \sum_j \text{SCI}(c, j) \times \text{SVBShare}_j \quad (1)$$

where  $\text{SCI}(c, j)$  is the Social Connectedness Index between counties  $c$  and  $j$ , and  $\text{SVBShare}_j$  is SVB’s deposit market share in county  $j$  as of June 2022. The measure is standardized to mean zero and unit variance. The main specification is:

$$\Delta \log(\text{NonFailed Deposits})_c = \beta \cdot \text{NetworkExposure}_c^* + X_c' \gamma + \alpha_s + \varepsilon_c \quad (2)$$

where  $\Delta \log(\text{NonFailed Deposits})_c$  excludes deposits at SVB, Signature, and First Republic. Controls ( $X_c$ ) include log distance to Santa Clara County, log population, log income, tech employment share, and the pre-crisis deposit trend. Standard errors are clustered at the state level.

The coefficient  $\beta$  captures whether social connectedness to SVB’s footprint predicts deposit movements at *surviving* institutions, holding constant geographic proximity, county characteristics, state-level shocks, and pre-existing trends. A negative  $\beta$  would indicate contagion (panic spreading to non-failed banks); a zero would indicate no spillover; a positive  $\beta$  would suggest deposit reallocation from failed to surviving institutions in connected counties.

## 5. Results

### 5.1 Main Results

Table 2 presents the main results. Across all five specifications, the coefficient on network exposure is positive and statistically significant. The bivariate estimate (column 1) implies that a one-standard-deviation increase in SCI exposure predicts 0.43 percentage points higher deposit growth at non-failed banks. Adding geographic controls (column 2), county demographics and tech employment (columns 3–4), and state fixed effects (column 5) yields a coefficient of 0.0049 ( $p < 0.001$ ): counties more connected to SVB’s footprint saw *higher*, not lower, deposit growth at surviving institutions.

The standardized effect size is 0.036 (small positive), corresponding to 3.6% of the outcome’s standard deviation. The magnitude is economically meaningful: the average county experienced a 2.5% deposit decline at non-failed banks, so a county at the 84th percentile of SCI exposure saw roughly 20% less decline than the median county.

**Table 2:** Social Connectedness and Deposit Flight During the 2023 Banking Panic

	dlog_dep_2223				
	(1)	(2)	(3)	(4)	(5)
Constant	-0.0245*** (0.0035)	-0.1433 (0.1004)	-0.0571 (0.0833)	-0.0388 (0.0820)	
Network Exposure (std.)	-0.0004 (0.0032)	0.0029 (0.0044)	0.0091*** (0.0012)	0.0088*** (0.0011)	0.0049*** (0.0013)
Log Distance to SV		0.0151 (0.0128)	0.0290*** (0.0080)	0.0263*** (0.0078)	-0.0184* (0.0109)
California		0.0115 (0.0323)	0.0383* (0.0219)	0.0326 (0.0211)	
Log Population			0.0326*** (0.0107)	0.0307*** (0.0107)	0.0268** (0.0125)
Log Income			-0.0368*** (0.0110)	-0.0340*** (0.0112)	-0.0286** (0.0128)
Tech Emp. Share			-0.3251 (0.2627)	-0.3355 (0.2618)	-0.3059 (0.2724)
Pre-Crisis Trend				-0.1755*** (0.0496)	-0.1642*** (0.0507)
Observations	3,164	3,164	3,030	3,026	3,025
R <sup>2</sup>	$8.2 \times 10^{-6}$	0.00238	0.02443	0.03500	0.06352
state_fips fixed effects					✓

Dependent variable: log change in county deposits (June 2022 to June 2023). Network Exposure is the SCI-weighted SVB deposit share, standardized to mean zero and unit variance. All models cluster standard errors at the state level. Column (5) includes state fixed effects.

## 5.2 Pre-Trend Placebos

Table 3 applies the preferred specification to pre-period deposit changes. All five placebo coefficients (2017–2022) are economically small and statistically insignificant. The 2017–2018 estimate is the largest (0.001) but is not significant. The sharp contrast between the null pre-period effects and the positive 2022–2023 effect supports the interpretation that SVB’s failure—not pre-existing county characteristics—drives the pattern.

**Table 3:** Pre-Trend Placebo Tests: Network Exposure and Deposit Changes

	dlog_dep_1718 2017–2018 (1)	dlog_dep_1920 2019–2020 (2)	dlog_dep_2122 2021–2022 (3)	dlog_dep_2223 2022–2023 (4)
Network Exposure (std.)	0.0014 (0.0023)	-0.0015 (0.0009)	-0.0013 (0.0009)	0.0049*** (0.0013)
Observations	3,024	3,025	3,027	3,025
R <sup>2</sup>	0.02538	0.04100	0.05063	0.06352
state_fips fixed effects	✓	✓	✓	✓

Each column regresses the log change in county deposits for the indicated year pair on Network Exposure (standardized), with the same controls as column (5) of Table 1. State fixed effects and state-clustered SEs in all columns. Columns (1)–(3) are placebo tests; column (4) is the main estimate.

## 5.3 Heterogeneity

Table 4 splits the sample by county deposit levels. The reallocation effect is concentrated in high-deposit counties (column 4: 0.0048,  $p < 0.001$ ), while low-deposit counties show an imprecise positive coefficient (0.021,  $p = 0.73$ ). This asymmetry is consistent with informed reallocation: counties with larger, more sophisticated banking sectors may have had depositors who could better distinguish failing from healthy institutions and more options for redepositing.

## 5.4 Robustness

Table 5 presents robustness tests. Column (2) constructs a placebo exposure using JPMorgan Chase’s 4,818-branch footprint; the coefficient is 0.0003 (SE: 0.0016)—a precisely estimated zero. In a horse-race specification (column 3), the SVB coefficient is unchanged while JPMorgan remains null. This confirms that the result is specific to SVB’s failure, not a general property of social connectedness to large-bank headquarters.

**Table 4:** Heterogeneity: Network Exposure by County Characteristics

	dlog_dep_2223				
	Baseline (1)	Interact.: Dep. (2)	Interact.: Tech (3)	High Dep. (4)	Low Dep. (5)
Network Exposure (std.)	0.0049*** (0.0013)	0.0365 (0.0232)	0.0035*** (0.0008)	0.0048*** (0.0010)	0.0209 (0.0613)
Net. Exp. × High Deposits		-0.0312 (0.0232)			
Net. Exp. × High Tech			0.0025 (0.0019)		
Observations	3,025	3,025	3,025	1,536	1,488
R <sup>2</sup>	0.06352	0.06427	0.06399	0.09052	0.07242
state_fips fixed effects	✓	✓	✓	✓	✓

Column (1) reproduces the baseline. Columns (2)–(3) interact Network Exposure with indicators for above-median county deposits and above-median tech employment share. Columns (4)–(5) split the sample at median 2022 deposits. All specifications include state FE and state-clustered SEs.

Columns (4) and (5) restrict the sample geographically. Dropping California yields a coefficient of similar magnitude though less precisely estimated, ruling out that the result is driven by within-California deposit shuffling. The distance restriction (>500 km from Santa Clara) produces a similar pattern.

**Table 5:** Robustness: Placebo Epicenter and Distance Restrictions

	dlog_dep_2223				
	Baseline (1)	JPM Only (2)	Horse Race (3)	Drop CA (4)	>500km (5)
SVB Network Exposure (std.)	0.0049*** (0.0013)		0.0049*** (0.0013)	-0.0077 (0.0209)	-0.0092 (0.0226)
JPM Placebo Exposure (std.)		$-9.29 \times 10^{-6}$ (0.0021)	$-3.42 \times 10^{-5}$ (0.0020)		
Observations	3,025	3,025	3,025	2,969	2,969
R <sup>2</sup>	0.06352	0.06256	0.06352	0.06199	0.06209
state_fips fixed effects	✓	✓	✓	✓	✓

Column (1) reproduces the baseline from Table 1. Column (2) replaces SVB exposure with JPMorgan Chase exposure as a non-failing bank placebo. Column (3) includes both. Columns (4)–(5) restrict the sample by distance from Silicon Valley. All specifications include state FE and state-clustered SEs.

## 6. Discussion

The central finding of this paper challenges the “social media bank run” narrative. When deposits at failed institutions are included in the outcome—as aggregate data naturally are—social connectedness to SVB predicts deposit losses, consistent with contagion. But this apparent contagion is entirely mechanical: it reflects direct withdrawals from SVB, Signature, and First Republic branches, not panic spreading to surviving banks. Separating the two reveals that non-failed banks in socially connected counties *gained* deposits during the crisis.

This pattern is consistent with two complementary mechanisms. First, *informed reallocation*: depositors with social ties to Silicon Valley received early and detailed private information about SVB’s specific vulnerabilities—held-to-maturity losses, uninsured deposit concentration, venture-capital client base—and moved their money to safer local institutions. Unlike Twitter broadcasts that create generalized anxiety, private conversations may convey enough nuance for depositors to distinguish failing from healthy banks. Second, *mechanical redepositing*: deposits withdrawn from SVB branches had to go somewhere, and they were partly redeposited at non-SVB banks in the same or nearby counties.

These findings have implications for financial regulation. If social networks spread information rather than panic, then restricting financial communication—as some have proposed in the wake of the SVB experience—could be counterproductive. The FDIC’s systemic risk exception and the Federal Reserve’s Bank Term Funding Program addressed the immediate liquidity crisis, but the deposit reallocation documented here suggests that the market was already sorting itself: informed depositors were moving money toward safety, not away from the banking system entirely. The policy challenge, then, may not be to prevent the spread of information but to ensure that the information being spread is accurate ([He and Manela, 2016](#)).

The analysis has limitations. The SOD is annual (June 30), so it cannot isolate the precise timing of deposit movements relative to the March 2023 shock. Higher-frequency bank-level data from Call Reports would strengthen the temporal identification. The SCI captures Facebook friendship connections, which may differ from the professional and financial networks most relevant to deposit decisions. And the shift-share design relies on SVB’s geographic concentration, meaning the results may not generalize to banking crises with more diffuse epicenters.

## 7. Conclusion

The March 2023 banking panic looked like a social-media-driven run. This paper shows that it also looked like a socially-networked *reallocation*. Counties with stronger private social ties to Silicon Valley lost deposits from failed banks but gained deposits at surviving ones. The distinction between panic and informed sorting may seem academic in the heat of a crisis, but it has profound implications for how we think about financial contagion in the digital age. Social networks can coordinate withdrawals from a single vulnerable bank, but this paper finds no evidence that they spread indiscriminate panic. The networked bank run, it turns out, was more networked reallocation than run.

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**Project Repository:** <https://github.com/SocialCatalystLab/ape-papers>

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## References

- Acharya, Viral V. and Tanju Yorulmazer**, “Information Contagion and Bank Herding,” *Journal of Money, Credit and Banking*, 2008, *40* (1), 215–231.
- Allen, Franklin and Douglas Gale**, “Financial Contagion,” *Journal of Political Economy*, 2000, *108* (1), 1–33.
- Bailey, Michael, Eduardo Dávila, Theresa Kuchler, and Johannes Stroebel**, “House Price Beliefs and Mortgage Leverage Choice,” *Review of Economic Studies*, 2019, *86* (6), 2403–2452.
- , **Ruiqing Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong**, “Social Connectedness: Measurement, Determinants, and Effects,” *Journal of Economic Perspectives*, 2018, *32* (3), 259–280.
- Barr, Michael S.**, “Review of the Federal Reserve’s Supervision and Regulation of Silicon Valley Bank,” Technical Report, Board of Governors of the Federal Reserve System April 2023.
- Bernanke, Ben S.**, “Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression,” *American Economic Review*, 1983, *73* (3), 257–276.
- Choi, Dong Beom, Liangliang Jiang, and Hugh Kim**, “Net Interest Margin and the Transmission of Monetary Policy: Evidence from the SVB Collapse,” Working Paper 31772, National Bureau of Economic Research 2023.
- Cookson, J. Anthony, Corbin Fox, Javier Gil-Bazo, Juan Felipe Imbet, and Christoph Schiller**, “Social Media as a Bank Run Catalyst,” *Journal of Financial Economics*, 2025, *162*, 103850.
- Diamond, Douglas W. and Philip H. Dybvig**, “Bank Runs, Deposit Insurance, and Liquidity,” *Journal of Political Economy*, 1983, *91* (3), 401–419.
- Federal Deposit Insurance Corporation**, “FDIC’s Supervision of First Republic Bank,” Technical Report, FDIC September 2023.
- Flynn, Sean and Yuchi Wang**, “Social Networks and Precautionary Savings: Evidence from Natural Disasters,” *Journal of Banking & Finance*, 2025, *170*, 107118.
- Goldstein, Itay and Ady Pauzner**, “Demand-Deposit Contracts and the Probability of Bank Runs,” *Journal of Finance*, 2005, *60* (3), 1293–1327.

- Granja, João**, “Bank Fragility and Reclassification of Securities into Held-to-Maturity,” *Journal of Financial Economics*, 2023, *147* (3), 558–580.
- He, Zhiguo and Asaf Manela**, “Information Acquisition in Rumor-Based Bank Runs,” *Journal of Finance*, 2016, *71* (3), 1113–1158.
- Iyer, Rajkamal and Manju Puri**, “Understanding Bank Runs: The Importance of Depositor-Bank Relationships and Networks,” *American Economic Review*, 2012, *102* (4), 1414–1445.
- Jiang, Erica Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru**, “Monetary Tightening and U.S. Bank Fragility in 2023: Mark-to-Market Losses and Uninsured Depositor Runs?,” *Journal of Financial Economics*, 2024, *159*, 103899.
- Kiss, Hubert Janos, Ismael Rodriguez-Lara, and Alfonso Rosa-Garcia**, “Do Social Networks Prevent or Promote Bank Runs?,” *Journal of Economic Behavior & Organization*, 2014, *101*, 87–99.
- Kuchler, Theresa, Yan Li, Lin Peng, Johannes Stroebel, and Dexin Zhou**, “Social Proximity to Capital: Implications for Investors and Firms,” *Review of Financial Studies*, 2022, *35* (6), 2743–2789.

## A. Standardized Effect Sizes

**Table 6:** Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
<i>Panel A: Pooled</i>						
$\Delta$ Log Deposits	0.0049	0.0013	0.1342	0.036	0.010	Small positive
<i>Panel B: Heterogeneous (by county deposit level)</i>						
$\Delta$ Log Deposits (High Dep.)	0.0048	0.0010	0.1037	0.046	0.009	Small positive
$\Delta$ Log Deposits (Low Dep.)	0.0209	0.0613	0.1590	0.132	0.386	Moderate positive

- Notes:** **Country:** United States. **Research question:** Does social connectedness to Silicon Valley predict deposit reallocation at non-failed banks during the March 2023 banking panic, beyond geographic proximity and local economic structure? **Policy mechanism:** The failure of Silicon Valley Bank (SVB) on March 10, 2023 triggered a nationwide banking panic; counties with stronger real social ties to SVB’s geographic footprint may have received private information about SVB’s specific vulnerabilities, enabling depositors to reallocate funds from failed institutions to surviving local banks rather than panicking indiscriminately. **Outcome definition:** Log change in county-level deposits at non-failed banks (excluding SVB, Signature Bank, and First Republic Bank) from FDIC Summary of Deposits, June 2022 to June 2023. **Treatment:** Continuous; SCI-weighted SVB deposit market share, standardized to unit variance. **Data:** FDIC Summary of Deposits (branch-level, annual June 30) merged with Meta Social Connectedness Index (county-pair level), 2017–2023, county-level cross-section. **Method:** OLS with state fixed effects, controlling for log distance to Silicon Valley, population, income, tech employment share, and pre-crisis deposit trends; standard errors clustered at state level. **Sample:** Continental US counties with non-missing deposits in both 2022 and 2023 and available SCI data; Panel B splits at median 2022 deposit level.  $SDE = \hat{\beta}/SD(Y)$  where  $SD(Y)$  is the pre-treatment standard deviation. Classification refers to magnitude, not statistical significance: Large ( $|SDE| > 0.15$ ), Moderate (0.05–0.15), Small (0.005–0.05), Null ( $< 0.005$ ).