RESEARCH ARTICLE

Business Intelligence Adoption and Financial Performance Among U.S. Small and Medium-Sized Enterprises: A Twelve-Month Longitudinal Panel Study

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Abstract

Background: Business intelligence (BI) technologies promise better resource allocation, faster analytical decision-making and improved operating performance. Yet evidence linking the timing of BI activation to financial outcomes in smaller enterprises remains limited, especially when permanent differences between firms and common economic conditions are considered.

Objective: To examine longitudinal associations between BI activation and revenue, operating profitability, net profitability and operating cash-flow intensity among U.S. micro, small and medium-sized enterprises during 2021.

Methods: A balanced monthly panel comprising 360 enterprises and 4,320 firm-month observations was analysed. Of these enterprises, 211 became BI-active between March and November, whereas 149 remained non-adopters throughout the observation period. Firm and calendar-month fixed-effects models adjusted for contemporaneous employment, COVID-19 disruption, regional demand and business opening days, with standard errors clustered by enterprise. A first-difference model and an exploratory event-time analysis assessed consistency and temporal patterns.

Results: BI-active status was associated with higher monthly revenue (log coefficient 0.0306; 95% CI 0.0178–0.0433; $p<0.001$), corresponding to approximately 3.1% higher revenue. Operating margin was higher by 1.55 percentage points (95% CI 0.95–2.15) and net profit margin by 1.21 percentage points (95% CI 0.71–1.71). The operating cash-flow-to-revenue difference was not statistically conclusive (0.97 percentage points; 95% CI −0.82–2.76). A first-difference model also identified a positive association with revenue changes (log coefficient 0.0161; $p=0.016$).

Conclusion: The timing of BI activation was positively associated with revenue and accounting profitability within enterprises, although evidence for an immediate improvement in operating cash-flow intensity was weaker. These observational associations support further investigation of BI implementation, capability development and financial value realisation in smaller firms.

Keywords: business intelligence; small and medium-sized enterprises; digital transformation; longitudinal analysis; firm performance; revenue; profitability; fixed-effects models

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1. Introduction

Business intelligence has evolved from management reporting and data warehousing into a broad set of practices for converting operational data into information used in business decisions. Dashboards, integrated reporting platforms, data visualisation and predictive analytical tools can assist enterprises in identifying sales patterns, allocating staff and inventory, reviewing costs and detecting deviations from planned performance. The theoretical appeal of these capabilities is substantial, but the practical question is whether their use translates into measurable improvements in enterprise financial results [1, 2, 3]. The distinction between adopting a technological system and realising value from it is particularly important: technology acquisition is an input, whereas performance depends on the organisational processes through which information is interpreted and acted upon.

Smaller businesses provide an especially relevant environment for this question. Micro and small enterprises often have limited managerial layers, fewer specialist analysts and tighter cash constraints than larger corporations. These features may make accessible analytical tools attractive because even modest improvements in forecasting, customer management or expense control can influence performance. They may equally restrict implementation, since software subscriptions, staff training and integration work compete with immediate operating needs. Research on small-firm technology adoption suggests that organisational readiness, perceived benefits, external conditions and technical compatibility jointly shape technology assimilation [4, 5, 6].

The business value of information technology is not necessarily apparent from comparing adopters with non-adopters at a single point in time. Firms with sophisticated digital processes may be more likely to adopt BI and may also be more productive regardless of BI. Larger firms can afford better systems and possess capabilities that independently improve sales and profitability. A simple cross-sectional comparison therefore combines potential benefits of BI with pre-existing organisational advantages. The broader information-systems literature has highlighted this difficulty in attributing firm outcomes to technological investments without recognising complementary capabilities and context [7, 8, 9].

Prior empirical evidence provides grounds for expecting favourable performance associations. Research on data-driven decision-making identified an association between systematic use of data and productivity in large organisations [10]. Studies of business analytics have linked analytical capabilities with better supply-chain performance, customer management and firm outcomes, while also emphasising the importance of organisational alignment and dynamic capabilities [11, 12, 13, 14]. However, the size and composition of these effects may differ markedly in smaller enterprises, and financial measures may respond at different speeds. Improved sales forecasting might strengthen revenues relatively quickly, whereas operating cash flow can remain

sensitive to working capital, credit terms and implementation expenditures.

The year 2021 also offers an instructive economic setting because enterprises continued operating under heterogeneous pandemic-related disruption, reopening patterns and regional demand changes. These conditions might be related to both the decision to deploy analytical systems and changes in business outcomes. A longitudinal design that observes the same enterprises before and after BI activation, while accounting for common calendar-month movements and measured operating conditions, can reduce some of the ambiguity surrounding simple adopter–non-adopter comparisons. Such a design does not, by itself, eliminate time-varying selection or establish causal effects, but it provides a more informative basis for interpreting contemporaneous financial associations.

Accordingly, this study examines three related questions. First, how did BI activation spread across a panel of U.S. micro, small and medium-sized enterprises during 2021? Second, were months in which enterprises actively used BI associated with differences in revenue and accounting profitability after controlling for enterprise-specific characteristics and common temporal conditions? Third, did the observed association extend to operating cash-flow intensity, and was the revenue result consistent with an alternative first-difference specification? By treating BI use as a time-varying enterprise attribute and considering multiple financial outcomes, the analysis distinguishes the adoption decision from subsequent operating experience.

2. Theoretical background and research propositions

2.1. Organisational capabilities and the conversion of information into value

The resource-based view holds that durable performance differences arise from valuable organisational resources and their distinctive deployment, rather than from resource ownership alone [15]. Applied to BI, this reasoning implies that software is unlikely to constitute a unique competitive advantage unless it is combined with suitable data, managerial routines and employee skills. The dynamic-capabilities perspective extends this idea by emphasising organisations' capacity to sense changes, reconfigure resources and respond to changing environments [16]. Analytical information can support these activities by making operational signals more visible, although the capacity to respond remains dependent on management and implementation quality.

Research on analytics capability has repeatedly distinguished technical infrastructure from managerial and human capabilities [17, 13]. Information systems can improve the availability and timeliness of information, but organisational performance depends on decision processes that convert information into action. Elbashir, Collier and Davern [18] reported that the performance implications of BI arise through business processes, while Popovič et al. [19] emphasised the relevance of analytical decision culture. System quality, use, satisfaction and net benefits are also distinct dimensions in the established information-systems success framework [20]. These perspectives caution against interpreting every installed BI platform as equivalent to effective BI use.

Knowledge absorption offers a complementary mechanism. Firms must identify valuable information, assimilate it and apply it to organisational problems, a process associated with absorptive capacity [21]. For a smaller enterprise, a platform that consolidates transaction and expense data may reduce fragmentation, but meaningful gains require employees who can interpret the resulting information. Adoption is therefore viewed here as an observable stage in a broader capability-development process rather than the complete mechanism of value creation.

2.2. BI adoption in smaller enterprises and expected financial outcomes

Diffusion theory recognises that adoption differs across organisations according to perceived relative advantage, compatibility, complexity and other innovation characteristics [22]. Technology acceptance and use similarly depend on perceived utility, social processes and facilitating conditions [23]. The SME-focused literature finds that organisational resources and technical readiness matter for both adoption and subsequent performance [5, 24]. These factors may generate selection into BI adoption and are therefore relevant when interpreting group differences at baseline.

The most immediate accounting channels plausibly connect BI with sales decisions and operating margins. Improved reporting may help managers identify underperforming products, interpret customer purchasing behaviour, adjust marketing spending or respond to changes in demand. Financial reporting and integrated analytics may also increase the visibility of cost components. Nevertheless, revenue gains and margin gains are analytically different outcomes: higher sales may be achieved through discounting or additional spending, while profit margins can improve through cost control without substantial revenue growth. Studies of analytics adoption have documented this context dependence rather than a uniform performance return [25, 26, 27].

Operating cash flow provides a further test of whether improvements in accrual-based results are accompanied by immediate liquidity benefits. Cash collection periods, supplier payments and inventory commitments can vary independently of recognised profit. BI implementation may itself entail upfront expenditure or training demands, making the short-run cash relationship less straightforward. The analytical expectation is therefore that BI-active months may be associated with stronger revenue and profitability, whereas a contemporaneous cash-flow benefit is less certain. These are empirical propositions about associations, not assumptions of an identified treatment effect.

3. Methods

3.1. Study design and analytical population

The study employed a longitudinal observational panel design covering January through December 2021. The analytical unit was the enterprise-month. The balanced panel comprised 360 uniquely identified U.S. businesses observed during each of 12 consecutive months, yielding 4,320 records. The enterprises spanned the Midwest, Northeast, South and West census regions and ten recorded industry sectors, including retail trade, healthcare services, accommodation and food, professional services, construction and manufacturing. January employee counts classified 148 enterprises as micro (1–9 employees), 161 as small (10–49) and 51 as medium-sized (50–249).

Each enterprise carried a time-invariant identifier and baseline characteristics including location, industry, ownership, firm age, January employment, digital readiness, accounting-software use, e-commerce exposure, credit access and market competition. Monthly fields described BI activation, operational activity, demand, workforce size, financial statements and working-capital measures. The principal analytical comparison involved enterprise-months before and after BI activation, with non-adopting businesses contributing observations throughout 2021. No business was missing a monthly observation; the record structure contained no duplicate enterprise-month combinations.

BI adopter status was recorded for 211 enterprises (58.6%), while 149 enterprises (41.4%) did not activate BI within the study period. Among adopters, the first month of active BI use occurred between March and November 2021, allowing within-enterprise changes to be observed for different adoption schedules. Adopter designation and monthly activation were treated separately: designation identified enterprises that adopted during the year, whereas active status indicated whether BI use was recorded in a particular month.

3.2. Exposure, outcomes and covariates

The exposure was BI-active status, coded 1 when an enterprise was recorded as actively using BI during the observation month and 0 otherwise. Active BI categories included dashboard and reporting, integrated BI and predictive analytics. Platform category, primary use case, software expenses, training hours, usage hours and connected data sources were retained for contextual interpretation, but were not entered into the primary regression as adjustment

factors because these quantities were contingent on implementation and could represent downstream mechanisms rather than pre-existing confounders.

Four financial outcomes were specified. The primary outcome was the natural logarithm of monthly revenue in U.S. dollars, enabling coefficients to be interpreted approximately as proportional differences; exact percentage differences were calculated as $100 \times [\exp(\beta) - 1]$. The principal secondary outcomes were operating margin and net profit margin, expressed in percentage points. Operating margin represented operating profit divided by revenue, and net profit margin represented net profit divided by revenue. The fourth outcome, operating cash-flow intensity, was operating cash flow divided by revenue and multiplied by 100. This ratio facilitated comparison of liquidity generation across different-sized businesses without conflating cash-flow magnitudes with enterprise scale.

Time-varying covariates comprised the natural logarithm of monthly employee count, a monthly COVID-19 disruption score (1–5), a regional demand index with a base of 100 and business opening days per month. Employment was included because changes in workforce capacity may accompany revenue and expense movements; the disruption score and demand index represented measured environmental conditions; and opening days reflected operating exposure. Enterprise fixed effects absorbed time-invariant observed and unobserved characteristics such as baseline size category, sector and digital readiness. Month fixed effects captured calendar-wide shocks and seasonality. The analysis does not claim that these variables exhaust the full set of possible time-varying confounders.

3.3. Data validation and descriptive analysis

The panel structure was checked for unique enterprise-month identification, consistent month coverage and valid numeric ranges of the modelling variables. Financial identities were examined by comparing gross profit with revenue less cost of goods sold and operating profit with gross profit less operating expense. No discrepancies exceeding USD 0.10 were identified in either identity. All 4,320 records had non-missing revenue, monthly employee counts, BI-active status and values for the adjustment variables. The 360 missing month-on-month revenue growth observations corresponded to the first month of each enterprise and did not enter the models, as revenue levels rather than the recorded growth field formed the main outcome. Missing BI adoption dates belonged to the 149 non-adopting enterprises and were consistent with their status.

Baseline comparisons used one January record per enterprise, thus avoiding the inflation of baseline sample size through repeated monthly measurements. Continuous characteristics were summarised as means, and binary or categorical variables as proportions. Monthly adoption counts were computed using each firm's first BI-active month. Financial outcome means by BI-active and non-active observations were described separately, with the explicit recognition that such comparisons combine between-enterprise differences and changes over time and should not be interpreted as adjusted effects.

3.4. Longitudinal regression analysis

Separate two-way fixed-effects linear regressions were estimated for logarithmic revenue, operating margin, net profit margin and operating cash-flow intensity. The specification was $Y_{it} = \alpha_i + \lambda_t + \beta BI_{it} + \gamma X_{it} + \varepsilon_{it}$, where i denotes enterprise, t denotes calendar month, α_i is the enterprise effect, λ_t is the month effect, BI_{it} is monthly active BI use and X_{it} contains contemporaneous log employment, the COVID-19 disruption score, regional demand and opening days. This specification estimates a within-enterprise association net of common calendar movements, conditional on the measured covariates. The identifying variation comes from changes in active BI status among adopting enterprises relative to other observations in the panel.

Standard errors were clustered by enterprise to accommodate repeated within-enterprise observations, with two-sided tests and 95% confidence intervals. This approach reflects the dependence expected in panel observations and follows established guidance on robust inference for longitudinal and difference-in-differences analyses [28, 29, 30]. Results were reported as model coefficients, confidence intervals and p-values; margin coefficients represent percentage-point differences. The primary model includes month-specific fixed effects, rather than using a single linear time trend that could inadequately represent irregular changes across 2021.

As a sensitivity analysis, the revenue model was estimated in first differences: monthly changes in log revenue were regressed on changes in BI-active status and changes in the covariates, with calendar-month transition indicators and enterprise-clustered standard errors. This provides a related but distinct estimate that places weight on changes between consecutive months, particularly the transition into BI use. It helps evaluate whether the direction of association persists under an alternative transformation of enterprise-specific time-invariant heterogeneity.

An exploratory event-time specification additionally replaced the single BI indicator with indicators for months relative to each adopting enterprise's first BI-active month, using the month immediately preceding activation as the reference. Relative-time periods four or more months before activation and five or more months after activation were grouped because observations become less numerous at the extremes. The coefficients were estimated with enterprise and month effects and the same time-varying covariates. They provide a visual description of temporal associations and a limited examination of pre-activation patterns. Conventional two-way fixed-effects event studies with staggered adoption can be affected by heterogeneous effects and comparisons involving already-treated units; consequently, these coefficients were not treated as independently identified dynamic causal effects [31, 32, 33].

4. Results

4.1. Enterprise characteristics and selection into adoption

Of the 360 enterprises, 211 adopted BI in 2021 and 149 remained non-adopters. The cohort comparison indicated meaningful differences before activation. Adopting enterprises averaged 33.5 January employees compared with 23.1 among non-adopters. Their mean digital readiness scores were 3.23 versus 2.69, and 80.6% versus 61.7% reported accounting-software use. Adopters also exhibited higher January revenue (USD 585,290 versus USD 373,892) and were less often micro enterprises (33.6% versus 51.7%). These patterns show that adoption was not distributed independently of organisational capacity or initial financial scale. Table 1 presents the principal baseline characteristics.

4.2. Timing and mode of BI use

No enterprises were coded as BI-active in January or February. Active use began for 10 enterprises in March and rose to 39 in April, 62 in May, 100 in June, 139 in July, 173 in August, 187 in September and 206 in October. By November, 211 enterprises were active, with the count remaining unchanged in December. The dataset therefore contained 1,338 BI-active enterprise-months and 2,982 non-active enterprise-months, of which 1,194 were recorded before activation among eventual adopters and 1,788 came from the never-adopter cohort. Among the active enterprise-months, dashboard and reporting accounted for 701 observations, integrated BI for 465 and predictive analytics for 172. These categories reflect actual records of platform use rather than mutually exclusive firm-level counts across the year.

Figure 1 displays both the number of enterprises becoming newly active in each month and the cumulative number actively using BI. Activation was concentrated from April through August, yielding substantial variation in the duration of observed post-activation exposure. The progressive activation pattern supports longitudinal comparisons but also means that enterprises adopting later contribute comparatively short post-activation sequences.

4.3. Unadjusted differences in financial performance

Descriptive revenue and profitability varied considerably across the three observation categories shown in Table 2. Mean monthly revenue was USD 716,583 in BI-active enterprise-months, USD 657,558 in pre-activation months of eventual adopters and USD 440,188 among never-adopter observations. Operating margins averaged 15.53%, 11.28% and 15.92%, respectively, while net profit margins averaged 11.54%, 8.03% and 11.73%. The differences cannot be interpreted as the benefits of BI activation because pre-activation periods occur earlier in the year and adopting firms differ substantially from non-adopters in initial size and digital readiness.

The descriptive contrast illustrates why a multivariable within-enterprise analysis is necessary. Even after grouping observations by activation status, the comparison mixes initial differences in operating scale, seasonal changes in demand and the selection of relatively digitally prepared firms into adoption. Operating cash-flow intensity also differed across categories (18.39%, 12.25% and 16.07%), although such ratios are sensitive to collections and payments within particular months.

4.4. Adjusted panel associations and sensitivity analysis

Across fixed-effects models, active BI use was positively associated with both the scale of activity and accrual-based profitability (Table 3). The estimated coefficient for log monthly revenue was 0.0306 (95% CI 0.0178–0.0433; $p<0.001$), equivalent to an approximately 3.1% higher revenue level in BI-active months conditional on enterprise effects, month effects, employment, disruption, regional demand and opening days. For operating margin, the adjusted difference was 1.55 percentage points (95% CI 0.95–2.15; $p<0.001$). The net margin difference was 1.21 percentage points (95% CI 0.71–1.71; $p<0.001$). These outcomes indicate that higher recorded revenue was accompanied by a favourable accounting margin relationship rather than merely a change in sales volume.

The estimated cash-flow-to-revenue coefficient was positive but imprecise: 0.97 percentage points (95% CI −0.82 to 2.76; $p=0.287$). The interval includes both a modest negative association and a materially positive one, preventing a firm conclusion about contemporaneous cash-flow improvement. The data therefore support a more differentiated interpretation of financial value than a blanket claim of uniform gains in every performance measure. The models also identified negative associations between higher recorded COVID-19 disruption and revenue or accounting margins, consistent with the importance of measured environmental conditions.

The sensitivity model using first differences generated a positive BI transition coefficient of 0.0161 for monthly changes in log revenue (95% CI 0.0030–0.0292; $p=0.016$). The direction is consistent with the primary model, though the magnitude is smaller and the estimand emphasises between-month change rather than the average level difference across all active months. The agreement in sign across different transformations strengthens the descriptive case for a relationship between BI activation and revenue but does not eliminate the possibility of concurrent changes, anticipatory investments or other unmeasured determinants of adoption timing.

4.5. Temporal pattern around activation

Figure 2 presents exploratory event-time estimates for log revenue, measured relative to the month immediately before BI became active. The coefficients for three months and two months before activation were close to zero, and the pooled period four or more months earlier also showed no marked departure from the reference value. At the first active month, the log-revenue coefficient was 0.0181 (95% CI 0.0058–0.0304), with subsequent coefficients of 0.0256 after one month, 0.0310 after two months and 0.0453 after three months. The grouped estimate for five or more months after activation was 0.0493 (95% CI 0.0247–0.0738). These observations are compatible with a positive association emerging around activation and persisting over several months.

Interpretation must nevertheless remain cautious. A non-significant set of pre-activation coefficients cannot establish the counterfactual parallel-trends assumption, particularly when enterprises choose different adoption months. In addition, conventional two-way fixed-effects event-time coefficients can be distorted if associations differ across adoption cohorts. Figure 2 is therefore presented as a descriptive temporal diagnostic, not as proof that BI caused the observed financial changes.

5. Discussion

5.1. Principal findings and interpretation

This longitudinal analysis found a positive adjusted association between BI-active months and revenue, operating margin and net profit margin among 360 U.S. micro, small and medium-sized enterprises followed throughout 2021. The magnitude of the revenue association was approximately 3.1%, while operating and net profit margins were higher by 1.55 and 1.21 percentage points, respectively. A first-difference specification provided a directionally consistent revenue result. By contrast, the cash-flow-to-revenue estimate was too imprecise to support a clear conclusion. Taken together, these findings suggest that the measured financial relationship was evident in business activity and accrual-based earnings but not unequivocally reflected in near-term operating cash generation.

An important contribution of the analysis is the separation of adoption status from active use at the monthly level. A year-end binary comparison would classify all 211 eventual adopters alike, despite the substantial differences between adoption in March, June or November. The longitudinal structure instead captured the timing of operational activation and multiple pre- and post-activation observations. This makes it possible to absorb stable differences between enterprises, such as industry and permanent managerial characteristics, while adjusting for measured changes in local conditions. It also reduces the risk of mistaking the higher initial revenue of adopters for the entire BI-related association.

The baseline comparisons reveal a practical digital-adoption divide. Eventual adopters were larger, more digitally ready, more likely to use accounting software and generated greater January revenue than never-adopters. Such differences align with the view that adoption depends on a combination of technological readiness, organisational resources and anticipated benefits [4, 5, 6]. They also demonstrate that observed adoption is not randomly assigned. This finding has implications for both empirical research and managerial practice: a reported association after activation should not be confused with evidence that the same effect would be realised by every enterprise regardless of baseline capacity or implementation conditions.

The positive revenue relationship is theoretically consistent with analytics enabling more informed commercial and operational decisions. BI tools can consolidate transaction patterns, customer information and financial indicators in ways that reduce delays in identifying changes in demand. Prior studies have linked data-driven decision-making and analytics capability with productivity and firm performance [10, 14, 25]. The present results extend that line of enquiry by focusing on a 12-month financial panel of smaller enterprises rather than relying exclusively on perceived performance measures or large-company samples. Importantly, the empirical result concerns BI-active status; it does not identify which specific dashboard function, algorithm, organisational decision or employee behaviour generated the association.

The margin findings are similarly compatible with the proposition that informational capabilities support better allocation of resources. More timely reports might permit faster adjustments to staff deployment, inventory management or marketing expenditure. The fact that both operating and net margins moved in a favourable direction may indicate that the revenue relationship was not completely offset by contemporaneous operating costs. However, margin improvement should not be attributed to one specific channel without direct evidence of that channel. The available fields include detailed expense categories, but the present design was not structured to decompose the regression association into

independently identified sales, pricing and cost-control mechanisms. Such decomposition would require carefully specified mechanisms and adequate treatment of potentially endogenous intermediate variables.

The less conclusive cash-flow result is informative rather than contradictory. Operating cash flow and accounting earnings measure different aspects of financial health. Revenue may be recognised before customers pay, inventory can absorb working capital, and supplier payment schedules may change the timing of cash movements. Moreover, BI platforms can require implementation expenditure, training and continuing subscription expenses. A short observation period after adoption may be sufficient to identify changes in reported sales and profits but insufficient to establish stable liquidity effects. The wide confidence interval for cash-flow intensity suggests considerable variability and supports avoiding a claim that BI adoption reliably improves every financial outcome.

5.2. Relationship to the business intelligence literature

The results can be understood through a capability-based rather than a purely technology-centred account. The resource-based view predicts that performance reflects the configuration of organisational resources; dynamic-capability arguments emphasise the actions firms take in response to information [15, 16]. BI activation could be one observable expression of that configuration, but software use and organisational learning are not interchangeable. This distinction echoes Trieu's [3] review of value creation from BI systems and the theoretical work of Grover et al. [9], which locate digital value within business processes, managerial use and organisational contexts.

Evidence from Akter et al. [13] and Gupta and George [17] likewise highlights that technology, skills and management are complementary components of analytics capability. The baseline readiness differences observed here support this emphasis: the enterprises most likely to activate BI already possessed comparatively stronger digital infrastructure. It would therefore be premature to attribute the complete observed revenue association to software installation alone. A comprehensive account would examine data quality, training intensity, managerial decision rights, the extent of integration across functions and the maturity of analytical practices. Popovič et al. [19] similarly suggested that culture and maturity shape BI success, and Cohen and Levinthal's [21] concept of absorptive capacity provides a useful explanation for why access to information does not automatically yield benefit.

SME-focused evidence has also emphasised the importance of organisational and environmental determinants. Maroufkhani et al. [24] found that determinants of analytics adoption and related performance merit attention specifically within smaller firms, while Ghobakhloo et al. [5] outlined staged approaches to implementing technology successfully. The present analysis is compatible with these observations yet cannot replicate them directly because it focuses on observed activation and financial indicators rather than a detailed survey of adoption beliefs and capabilities. It should therefore be read as complementary longitudinal financial evidence rather than as a test of all elements of the technology–organisation–environment framework.

One methodological implication concerns event-time analysis. Staggered activation is appealing because it supplies variation in exposure timing, but recent econometric work makes clear that naïve two-way fixed-effects treatment effects can aggregate heterogeneous cohort comparisons in unintuitive ways [31, 33]. The approach used here explicitly reports conditional associations and treats the event-time display as exploratory. Future work with documented assignment and comparison strategies could apply cohort-specific group-time estimators, as developed by Callaway and Sant'Anna [32], to support stronger causal interpretation where their assumptions are defensible.

5.3. Practical implications

For managers, the findings support a disciplined distinction between acquiring BI software, achieving regular analytical use and obtaining financial value. Technology procurement should be accompanied by integration with operational data and clear responsibility for acting on business insights. A reporting platform can facilitate awareness of changing conditions; measurable performance improvements depend on the ability to translate that awareness into decisions about customers, pricing, inventory, labour and expenditure. The enterprise should therefore evaluate the actual decisions improved by BI rather than selecting a platform solely on the basis of functionality or promotional claims.

The readiness differences in this panel imply that less digitally mature firms may face greater barriers to implementation. For such firms, foundational accounting systems, consistent data definitions and staff proficiency may be necessary before advanced predictive tools offer substantial incremental benefit. Training should extend beyond producing dashboards to interpretation, decision-making and monitoring of results. Existing research suggests that capability and strategic alignment are important for performance realisation [13, 26]. The observation that dashboard and reporting systems accounted for a substantial share of active months also reinforces the relevance of comparatively accessible applications rather than an assumption that every smaller enterprise requires sophisticated modelling infrastructure.

Financial monitoring should use a balanced set of metrics. The positive adjusted associations with revenue and margins do not justify treating profit as a substitute for liquidity. Enterprises investing in BI may benefit from monitoring operating cash flow, receivable collection, inventory holding periods and implementation spending alongside accounting performance. Evaluation over a longer horizon would help distinguish temporary implementation burdens from sustained benefits. For advisers and policymakers supporting SME digitalisation, adoption assistance may be most valuable when it combines accessible technology with data-management skills and implementation support, rather than concentrating exclusively on software availability.

6. Conclusion

In a balanced 2021 panel of 360 U.S. micro, small and medium-sized enterprises, BI-active months were associated with approximately 3.1% higher monthly revenue, a 1.55-percentage-point higher operating margin and a 1.21-percentage-point higher net profit margin after controlling for stable enterprise differences, calendar month and measured operating conditions. The revenue relationship remained positive in a first-difference sensitivity analysis. In contrast, evidence for an improvement in operating cash-flow intensity was inconclusive.

These findings indicate that the period of active BI use coincided with favourable operating and accounting outcomes, but they do not establish that BI alone caused those differences. Digital readiness and firm scale differed appreciably between adopters and non-adopters, reinforcing the need to assess organisational capabilities alongside technology decisions. More detailed longitudinal evidence on implementation quality, managerial use and working-capital outcomes will help clarify how analytical technologies translate into sustainable value for smaller enterprises.

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Figures

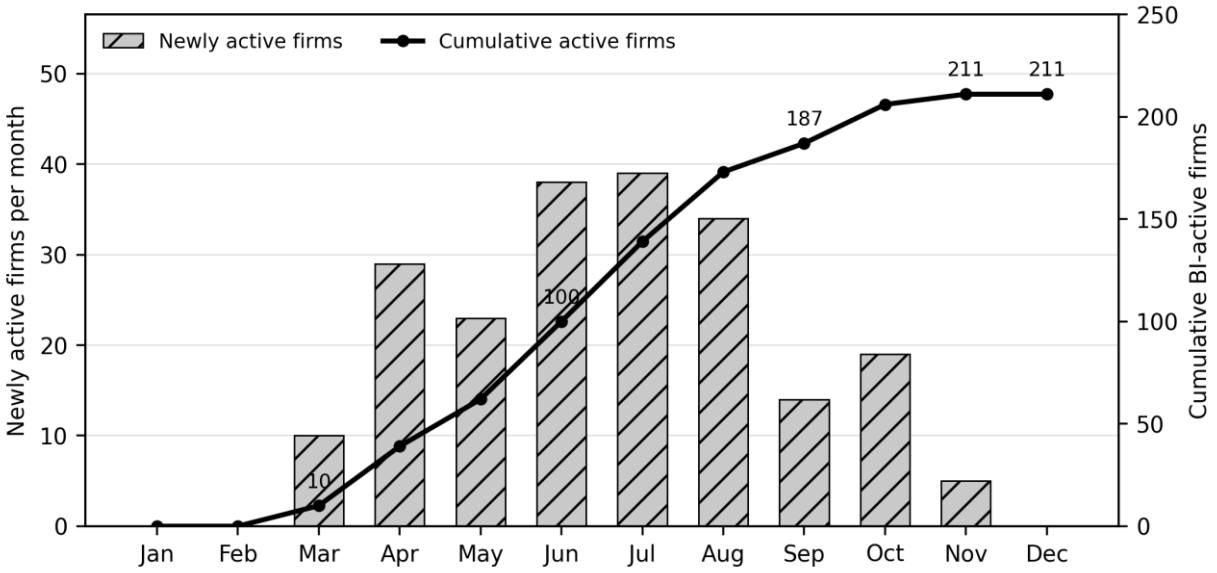


Figure 1. Monthly BI activation and cumulative number of BI-active enterprises, January–December 2021. Monthly counts reflect the first month of recorded active use.

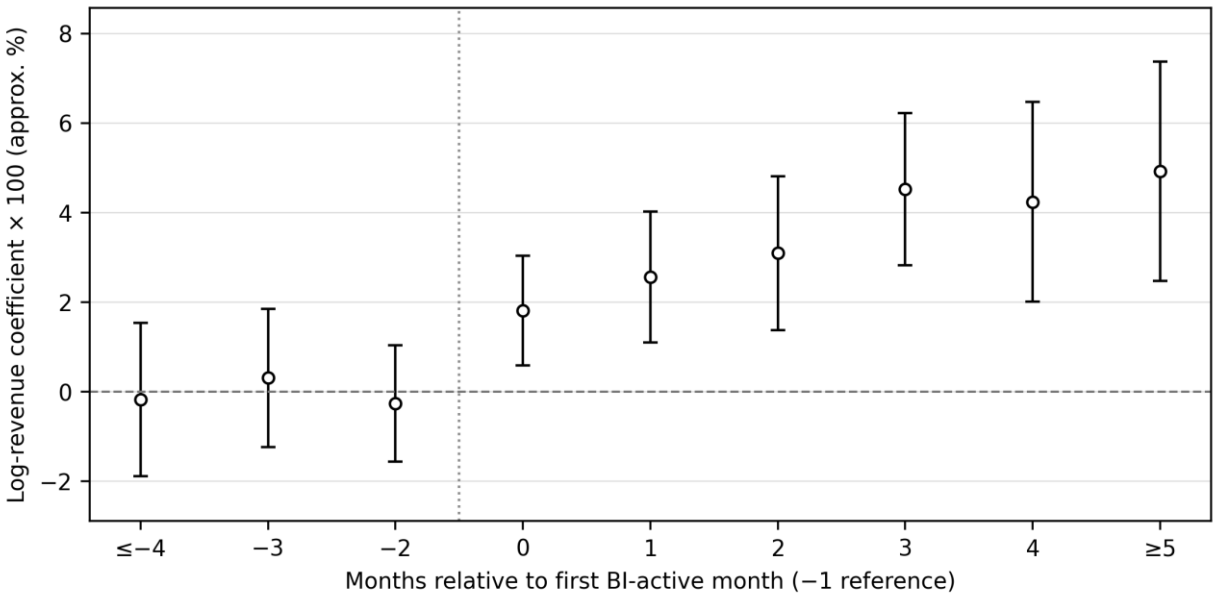


Figure 2. Exploratory event-time coefficients for monthly log revenue relative to the month immediately preceding BI activation. Points indicate adjusted estimates and whiskers show enterprise-clustered 95% confidence intervals. Estimates are descriptive rather than causally identified dynamic treatment effects.

Tables

Table 1. Baseline enterprise characteristics by BI adoption cohort

Characteristic	2021 adopters (n=211)	Non-adopters (n=149)
Number of employees	33.5	23.1
Firm age (years)	15.7	15.1
Digital readiness (1-5)	3.2	2.7
Accounting software in use (%)	80.6	61.7
E-commerce sales share (%)	31.5	28.0
Credit access (%)	85.3	78.5
Revenue in January (USD)	585,290	373,892
Micro firms (%)	33.6	51.7
Small firms (%)	48.8	38.9
Medium firms (%)	17.5	9.4
Urban firms (%)	46.4	48.3

Note. One January record was used per enterprise. Percentages are proportions of firms unless otherwise indicated; e-commerce sales share is a percentage. Values are descriptive and unadjusted.

Table 2. Unadjusted financial indicators by BI-active status of enterprise-months

Observation category	n	Revenue (USD)	Operating margin (%)	Net margin (%)	Cash-flow/revenue (%)
BI-active observations	1,338	716,583	15.53	11.54	18.39
Adopter observations before activation	1,194	657,558	11.28	8.03	12.25
Never-adopter observations	1,788	440,188	15.92	11.73	16.07

Note. Figures are means over enterprise-months. Categories are observation states, not independent groups of firms. Consequently, descriptive differences do not estimate BI effects.

Table 3. Two-way fixed-effects estimates of BI-active status and financial outcomes

Covariate / model feature	Log revenue	Operating margin (pp)	Net margin (pp)	Cash-flow ratio (pp)
BI-active month	0.031 (0.007)	1.553 (0.307)	1.210 (0.256)	0.971 (0.912)
Log monthly employees	0.094 (0.015)	-4.616 (0.687)	-3.609 (0.566)	-6.833 (2.262)
COVID-19 disruption index	-0.013 (0.002)	-0.556 (0.096)	-0.445 (0.079)	0.315 (0.439)
Regional demand index	0.007 (0.002)	0.249 (0.077)	0.210 (0.063)	-0.289 (0.352)
Business opening days	-0.000 (0.001)	-0.035 (0.025)	-0.025 (0.020)	-0.085 (0.127)
Firm fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Enterprise-month observations	4,320	4,320	4,320	4,320
Within R^2	0.051	0.050	0.046	0.003

Note. Coefficients are followed by enterprise-clustered standard errors in parentheses. Margin and cash-flow coefficients are in percentage points (pp). For BI-active status, the corresponding 95% CIs are 0.0178–0.0433, 0.95–2.15, 0.71–1.71 and −0.82–2.76, respectively. Results for log revenue are on the log scale.