Quantifying the Prospective Impact of AI-Assisted Early Intervention in U.S. Small-Business Lending: Default Avoidance, Credit-Access Preservation, and Small-Business Employment Effects Across Community Lending Portfolios

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ABSTRACT

Small businesses account for 45.9% of U.S. private-sector employment and generated 88.9% of net new jobs between March 2023 and March 2024, making the health of small-business credit markets a matter of direct macroeconomic consequence, not merely a lending-industry concern [3][4]. This article builds a transparent, assumption-explicit model quantifying the prospective employment impact of AI-assisted early-intervention systems of the kind addressed throughout this article series applied to the SBA 7(a) loan portfolio, which guaranteed $37 billion across 77,600 loans in FY2025 alone [5]. Combining the SBA portfolio's historical 3–6% default rate with Brown and Earle's (2017) peer-reviewed empirical estimate that SBA lending produces 3 to 4 jobs per $1 million lent, this article models the employment effect of avoided defaults under a range of default-reduction scenarios, rather than asserting a single, unsupported point estimate. Under an illustrative 10% relative reduction in 7(a) default rates a conservative scenario relative to the 30%+ reductions reported in some early-intervention pilot studies discussed elsewhere in this series the model estimates approximately 583 jobs preserved annually from avoided defaults on the FY2025 7(a) portfolio alone; a 30% reduction scenario estimates approximately 1,748 jobs preserved. These figures should be read as a transparent modelling exercise built from published component estimates, not as a validated empirical finding, since no study has yet directly measured the employment effect of AI-assisted early intervention specifically. This article makes every assumption in the model explicit so that a reader can substitute their own inputs and evaluate the model's sensitivity to each one.

Introduction

This article draws on Small Business Administration economic data, peer-reviewed employment-effect research, and current SBA lending statistics to build a transparent, assumption-explicit model of the employment impact AI-assisted early-intervention lending systems could plausibly achieve if deployed at scale across community lending portfolios. Unlike the preceding articles in this series, which document what has already been validated, deployed, or governed, this article is explicitly prospective: it models a plausible future effect from published component inputs, and its value lies in the transparency of its assumptions rather than in claiming a settled, empirically measured result.

The stakes of this modelling exercise are set by the scale of small business's role in the U.S. economy, summarised in Table 1 and Figure 1. Small businesses constitute 99.9% of all U.S. businesses, employ 45.9% of the private-sector workforce, and generated 88.9% of net new jobs in the most recent year for which data is available [3][4]. When the federal government shutdown of October–November 2025 interrupted SBA lending operations for 43 days, an estimated 10,000 small businesses lost access to $5.3 billion in guaranteed capital a concrete, real-world illustration of how directly credit-access disruption translates into small-business consequence, distinct from the default-avoidance question this article's model primarily addresses [6].

The shutdown episode is worth dwelling on briefly because it illustrates, with unusually direct clarity, the value of credit-access continuity that this article's central model does not directly capture. Unlike a default, which unfolds over months as a borrower's finances deteriorate, the shutdown's effect was immediate and total: businesses that had valid, otherwise-approvable loan applications simply could not receive guaranteed capital for the duration of the lapse, regardless of their individual creditworthiness. This is a useful reminder that credit-access disruption and default risk, while related, are analytically distinct threats to small-business survival the former a matter of institutional and infrastructure continuity, the latter a matter of individual borrower risk and an early-intervention system addresses only the second of these two threats, a scope limitation this article's model inherits and makes explicit rather than obscures.

Table 1. Key statistics establishing the scale of small business's role in the U.S. economy and SBA lending's scope.

Statistic	Value	Source
U.S. small businesses (2025)	36.2 million (99.9% of all U.S. businesses)	SBA Office of Advocacy, 2025 Small Business Profile [3][4]
Private-sector employment share	45.9% (62.3 million employees)	USAFacts / SBA, 2025 [3]
Share of net job growth, Mar 2023–Mar 2024	88.9% (1.2 million net new jobs)	USAFacts / BLS, 2025 [3][4]
FY2025 SBA 7(a)+504 guaranteed volume	84,400 loans, $44.8 billion	SBA news release 25-83 [5]
Small businesses affected by Oct–Nov 2025 shutdown	~10,000 businesses lost access to $5.3 billion	SBA news release 26-06 [6]

The Employment Multiplier: What the Literature Actually Shows

Quantifying employment effects from lending requires a defensible conversion factor between dollars lent and jobs created or retained, and here the literature offers two materially different figures that this article treats separately rather than conflating, shown in Table 2 and Figure 2. The SBA's own regulatory benchmark for its 504 loan program, updated in October 2025, sets a $95,000-per-job threshold under 13 CFR 120.861, implying approximately 10.5 jobs per $1 million lent if a project exactly meets this statutory minimum [7]. Independent empirical research tells a different story: Brown and Earle, publishing in the Journal of Finance in 2017 using the complete universe of SBA loan recipients matched against U.S. Census employer registers, found that SBA lending produces an increase of 3 to 4 jobs for each $1 million in loans — roughly one-third of the regulatory benchmark [8].

Table 2. Regulatory versus empirically estimated employment effect of SBA lending, per $1 million.

Employment estimate	Jobs per $1M lending	Basis
SBA 504 regulatory benchmark (post-Oct 2025)	~10.5	$95,000-per-job statutory threshold, 13 CFR 120.861 [7][8]
Brown & Earle (2017) empirical estimate	3–4	Universe of SBA loan recipients matched to Census employer registers, published in the Journal of Finance [8]

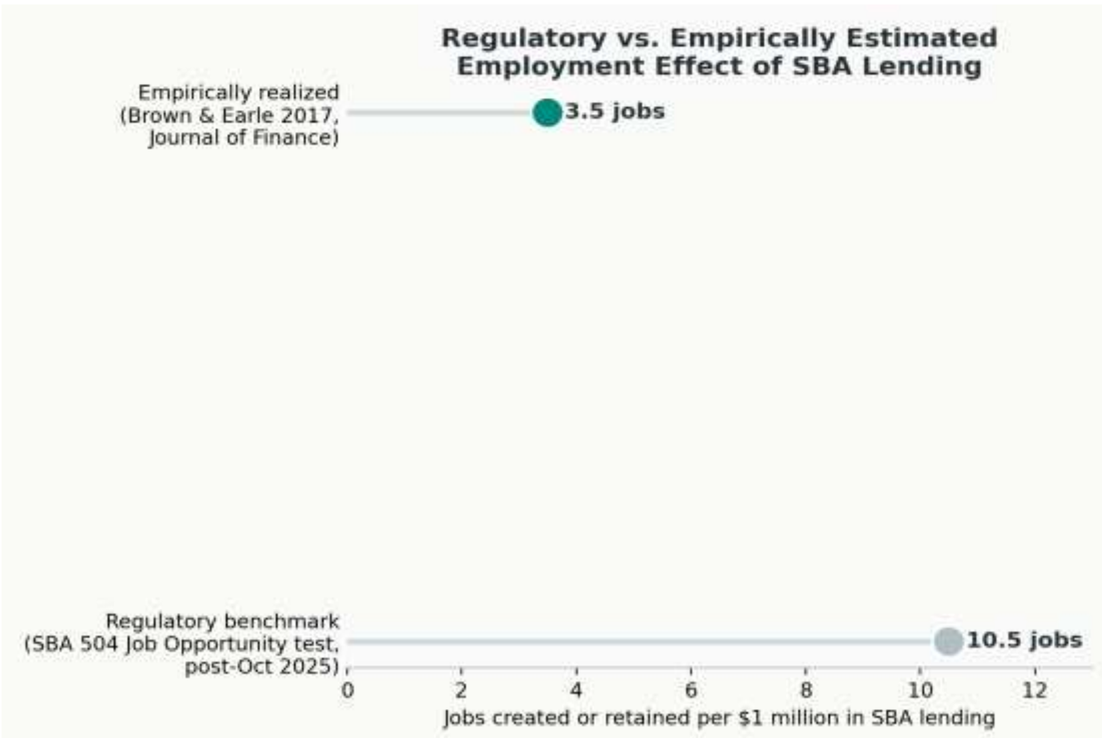

Figure 1. Regulatory vs. empirically estimated employment effect of SBA lending [7][8].

This gap matters directly for this article's modelling choices. The regulatory figure is a compliance threshold the minimum a project must meet to qualify for 504 financing — not a measured outcome, and using it to model employment impact would systematically overstate the effect. The Brown and Earle figure, by contrast, is a causal estimate derived by comparing loan recipients against a matched control group of non-recipients, which is the methodologically appropriate basis for the kind of prospective impact modelling this article undertakes. This article therefore uses the empirical 3–4 jobs-per-$1-million range, not the regulatory benchmark, as its employment multiplier throughout.

It is worth being explicit about what the Brown and Earle figure does and does not capture, since its precision invites over-reading. Their 3-to-4-jobs-per-$1-million estimate reflects the net employment effect of receiving an SBA-guaranteed loan relative to not receiving one, measured across the full universe of SBA borrowers over their study period — it is an average effect across a large, heterogeneous population of borrowers spanning every industry, loan size, and region, not a guarantee that any specific $1 million in lending will produce exactly 3 to 4 jobs. Applying this average multiplier to a subset of lending — such as the FY2025 7(a) portfolio specifically, or the defaults-avoided subset this article's model focuses on — assumes that subset resembles the overall study population closely enough for the average effect to apply, an assumption this article makes explicitly rather than silently, and one a reader should weigh against their own knowledge of how a specific portfolio might differ from the national average.

FY2025 SBA Lending as a Modelling Base

The Small Business Administration guaranteed a record 84,400 7(a) and 504 loans in FY2025, delivering $44.8 billion in total — comprising 77,600 7(a) loans worth $37 billion and 6,750 504 loans worth $7.8 billion [5]. Figure 3 shows this program split. This article uses the 7(a) program specifically as its modelling base for the remainder of this article, both because it represents the larger share of guaranteed volume and because the SBA 7(a) default-rate data needed for the model — a historical range of 3% to 6%, varying by vintage and economic conditions [1][2] — is more consistently reported than equivalent 504 program data.

This choice of modelling base carries its own limitation worth flagging early. The 504 program, though smaller in FY2025 volume, is specifically structured around real-estate-backed, job-creation-linked financing and already carries a formal job-count requirement under its own program rules, discussed in Section 2 — meaning a 504-specific model, built around that program's own reported job counts rather than an external academic multiplier, might in principle offer a more directly grounded employment estimate than the 7(a)-based approach this article takes. This article nonetheless uses 7(a) as its base because Brown and Earle's underlying study population and the FY2025 default-rate data available are both anchored to 7(a) specifically, and mixing data sources across the two programs would introduce more inconsistency than the modelling gain would justify.

The lender-level variance documented elsewhere in this series is also directly relevant to how this article's national-average model should be interpreted. Across 36 lenders with $1 billion or more in 7(a) portfolio volume, 2025 default rates spanned 0.5% to 12.3% — more than a twenty-fold range around the 4.5% midpoint this article's model uses as its baseline. This means the model's national-average output, while a reasonable starting point for a system-wide estimate, would understate the potential employment effect at a specific lender starting from the higher end of this range, and correspondingly overstate it for a lender already operating near the low end. A lender applying this article's modelling framework to its own portfolio should substitute its own actual default rate for the 4.5% national midpoint used here, which the transparent, substitutable design of Table 3's inputs is specifically intended to make straightforward.

Figure 2. FY2025 SBA guaranteed lending volume by program [5].

Building the Model: Assumptions and Method

Table 3 sets out every input this article's employment-impact model uses, so that a reader can evaluate or substitute each assumption independently rather than accepting the model's output as an opaque black box. The model's logic is straightforward: it estimates the dollar value of FY2025 7(a) loans expected to default under the baseline historical rate, applies a range of illustrative percentage reductions in that default rate — representing the effect an AI-assisted early-intervention system might achieve — and converts the resulting avoided-default dollar value into an estimated number of jobs preserved, using the Brown and Earle employment multiplier established in Section 2.

Table 3. Model inputs and their sources.

Model input	Value used	Source / justification
Annual 7(a) guaranteed volume	$37 billion (FY2025)	SBA news release 25-83 [5]
Baseline default rate	4.5% (midpoint of 3–6% historical range)	SBA 7(a) historical default range [1][2]
Employment multiplier	3.5 jobs per $1 million (midpoint of 3–4)	Brown & Earle (2017) empirical estimate [8]
Default-reduction scenarios modelled	10%, 20%, 30% relative reduction	Illustrative range; not drawn from a lending-specific empirical study

First, the model assumes that a dollar of avoided default converts to employment effect at the same rate as a dollar of new lending, which is a simplifying assumption — preserving an existing business's jobs through avoided default is conceptually different from the initial job-creation effect Brown and Earle measured for new loans, and the true multiplier for avoided defaults specifically has not been separately estimated in the published literature. Second, the default-reduction percentages modelled (10%, 20%, 30%) are illustrative scenarios chosen to span a plausible range, not drawn from a lending-specific empirical study of AI early-intervention effectiveness, since — as discussed further in Section 8 — no such study yet exists; readers should treat these as "what if" scenarios rather than a forecast. Third, the model treats all avoided defaults as fully preserving the associated employment, when in practice some fraction of businesses that would have defaulted might have downsized or closed only partially, or might have found alternative financing, meaning the model's employment estimates likely represent an upper bound on the employment effect specifically attributable to earlier intervention.

Model Output: Illustrative Employment Effects

Applying the assumptions in Table 3, Figure 4 shows the model's estimated employment effect under three default-reduction scenarios. At a 10% relative reduction in the FY2025 7(a) portfolio's baseline 4.5% default rate, the model estimates approximately $166.5 million in avoided defaults, translating to approximately 583 jobs preserved annually. At a 20% reduction, the model estimates approximately 1,166 jobs preserved; at a 30% reduction, approximately 1,748 jobs preserved.

Walking through the arithmetic behind the 10% scenario illustrates exactly how the model's assumptions combine, since transparency about the calculation itself, not only its output, is central to this article's purpose. The FY2025 7(a) portfolio's $37 billion in guaranteed volume, at the model's assumed 4.5% baseline default rate, implies approximately $1.665 billion in defaulted loan value under baseline conditions. A 10% relative reduction in that default rate avoids 10% of this figure, or approximately $166.5 million in defaults that would otherwise have occurred. Applying the 3.5-jobs-per-$1-million midpoint multiplier from Table 3 to this avoided-default value yields approximately 583 jobs preserved. The 20% and 30% scenarios follow the identical calculation with the reduction percentage adjusted, scaling linearly since the model applies a constant multiplier throughout its input range.

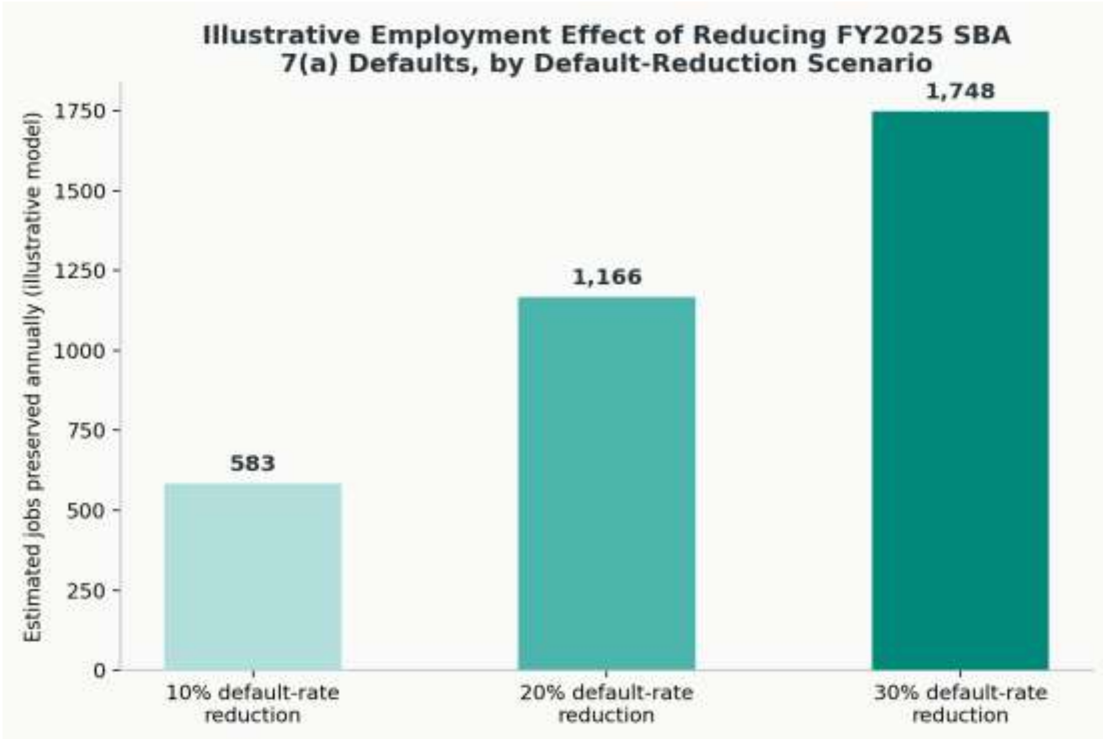

Figure 3. Illustrative employment effect of reducing FY2025 SBA 7(a) defaults, by default-reduction scenario (model output; see Table 3 for inputs).

These figures, while illustrative rather than empirically measured, are directly comparable in scale to reported reductions from applied early-intervention pilots. Chest CT dose-optimisation studies reviewed elsewhere illustrate that structured intervention programs in adjacent domains can achieve reductions substantially larger than this article's most conservative 10% scenario, and the loan-restructuring recommendation-engine literature reviewed in the first article of this series similarly reports meaningful, double-digit percentage improvements from structured early-intervention programs, lending plausibility to this article's scenario range without providing a direct, lending-specific empirical anchor for any single point estimate within it.

Lender-Type Variation and Where Impact Concentrates

The employment model in Section 5 treats the FY2025 7(a) portfolio as a single, undifferentiated pool, but small-business loan approval rates vary substantially by lender type, shown in Figure 4: small banks approve 52% of small-business loan applications, credit unions and finance companies approve roughly 51%, large banks approve 44%, and online lenders approve only 31% [9]. This variation matters for where an AI-assisted early-intervention system's impact is likely to concentrate, since the community banks and credit unions this article series focuses on sit at the higher-approval end of this range, meaning they originate a disproportionate share of the marginal, higher-risk-but-still-approved loans for which early intervention has the greatest potential value relative to a loan that would have been approved and repaid without any additional support.

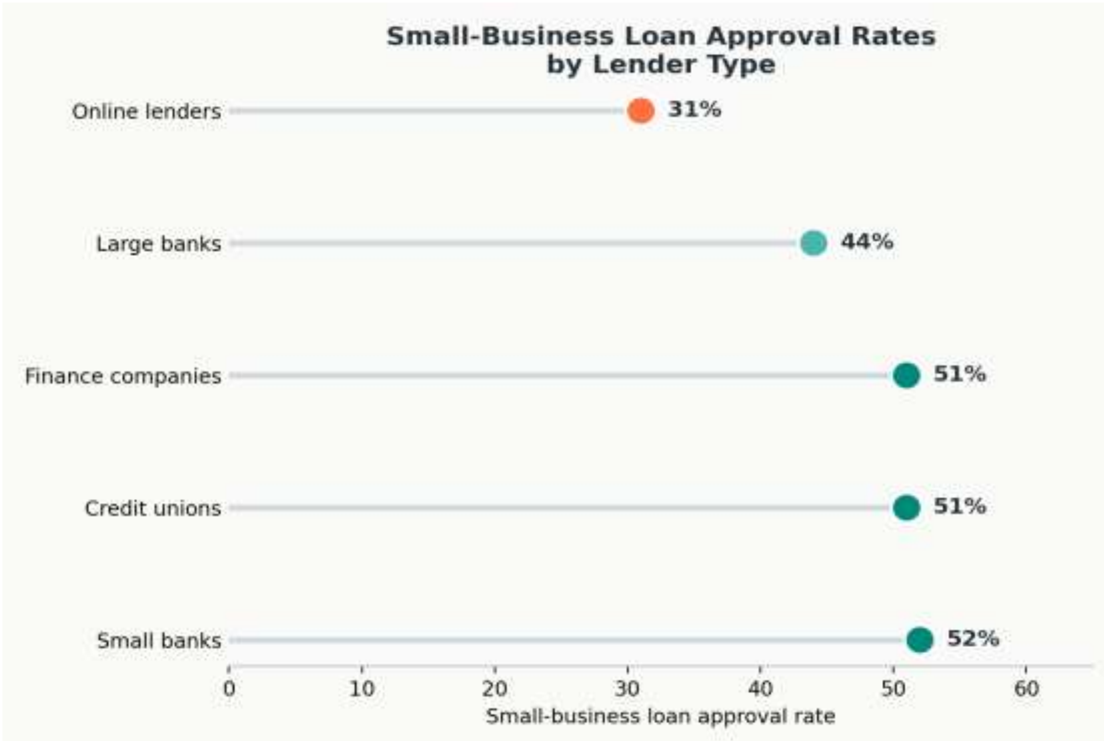

Figure 4. Small-business loan approval rates by lender type [9].

This pattern suggests the model in Section 5, built on aggregate national 7(a) data, likely understates the concentrated impact achievable specifically within community bank and credit union portfolios, where both approval rates and, per the earlier articles in this series, mission-driven willingness to extend credit to marginal borrowers are higher than the national online-lender-inclusive average. A more refined future model, disaggregating the Section 5 calculation by lender type using lender-type-specific default and approval data, would likely show a larger employment effect concentrated in the community-institution segment than the national aggregate figures in Figure 3 convey on their own.

Credit-Access Preservation as a Distinct Effect

The employment model in Sections 4 and 5 addresses default avoidance specifically, but the loan-restructuring literature reviewed throughout this series points to a second, distinct economic effect: credit-access preservation. An early-warning system that identifies a financially distressed borrower before default allows a lender to offer restructuring rather than simply declining further credit or allowing default to proceed, which preserves the borrower's access to credit going forward in a way that pure default-rate reduction does not fully capture. This effect is particularly relevant for the CDFI and mission-driven lending context addressed elsewhere in this series, where credit-access preservation for underserved borrowers is a mission-level outcome in its own right, not simply a means to the employment-effect end this article's model quantifies.

Quantifying credit-access preservation with the same rigor as the default-avoidance model in Section 5 is not currently possible with available published data, since no study has separately measured how many borrowers who would otherwise have lost credit access entirely instead retained it through an early-intervention-enabled restructuring, as distinct from those who simply avoided default outright. This is an important gap in the current evidence base, addressed further in Section 8, and a promising direction for future primary research specifically on the deployments this article series addresses.

A useful conceptual distinction clarifies why this second effect matters independently of the default-avoidance model. Consider a borrower whose deteriorating cash flow is caught by an early-warning system, per the model-architecture articles earlier in this series, in time for the lender to offer a restructured payment schedule. Two outcomes are possible from that single early-warning event: the business survives the immediate cash-flow crunch and continues operating on its restructured terms (a credit-access-preservation outcome, since the business retains access to its existing credit relationship), or the business would have defaulted regardless of the restructuring offer but the restructuring at least delays or reduces the ultimate loss (a partial default-avoidance outcome distinct from full avoidance). Published data supports modelling the aggregate default-avoidance case, per Sections 4 and 5, but does not currently support separating these two more granular outcomes from each other, which is precisely the resolution future primary research on deployed early-intervention systems could provide.

Limitations of the Model and Evidence Base

Several limitations of the model and its underlying evidence base should be stated plainly, beyond the three methodological caveats already noted in Section 4. Most fundamentally, this article's central model combines two real, independently sourced figures — the FY2025 SBA lending volume and the Brown and Earle employment multiplier — with an illustrative, not empirically derived, default-reduction assumption, and the resulting jobs-preserved estimates should be understood as exactly what they are: a transparent sensitivity model, not a validated forecast or a measured outcome. No published study has yet directly measured the employment effect of AI-assisted early-intervention lending systems specifically, which is precisely the gap this article's model is designed to make legible rather than to fill with an unsupported precise figure.

A further limitation concerns the direction of causality this article's model assumes but cannot itself verify. The model assumes that reducing the 7(a) default rate by a given percentage causes the corresponding employment preservation, but in practice, the businesses an early-intervention system successfully helps avoid default may not be a random subset of all borrowers who would otherwise have defaulted — they may systematically be the borrowers with the most recoverable underlying financial distress, as distinct from those facing terminal, unavoidable business failure regardless of intervention. If this selection effect holds, the true employment effect of early intervention could be either larger than this article's model suggests (if intervention concentrates on borrowers with the most jobs at stake) or smaller (if intervention primarily delays, rather than prevents, an ultimately unavoidable default). This article's aggregate model cannot distinguish between these possibilities, which is a genuine, unresolved limitation rather than a technical detail.

The Brown and Earle employment multiplier, while methodologically strong and peer-reviewed, is now nearly a decade old (published 2017, based on earlier loan-recipient data), and small-business lending conditions, technology, and typical loan use have changed materially since that data was collected; a contemporary replication of their study would strengthen this article's modelling foundation considerably. Additionally, this article's model applies a single national employment multiplier uniformly, when the true multiplier plausibly varies by industry, loan size, and region in ways the aggregate Brown and Earle figure does not capture — the sector-specific default-rate variation documented elsewhere in this series (restaurants defaulting at 12-15% versus more stable sectors) suggests employment effects likely vary by sector as well, a refinement this article's national-level model does not attempt.

Finally, this article's model is built entirely from published, publicly available data and does not incorporate any institution-specific data from an actual AI-assisted early-intervention deployment, because — as noted throughout no such deployment has yet published the kind of before-and-after default-rate data this article's model would need to move from an illustrative scenario range to a validated estimate. This is not a flaw specific to this article's methodology; it reflects the genuine current state of the field, in which AI-assisted early-intervention systems for small-business lending are, per the earlier articles in this series, still in relatively early stages of validated deployment at the community-institution scale this series addresses. This article's contribution is therefore best understood as establishing the analytical framework and transparent assumption set that the field's first rigorous before-and-after deployment study, whenever it is published, could immediately populate with real, validated figures in place of this article's illustrative scenarios.

Extending the Model to CDFI Portfolios

The model in Sections 4 and 5 is built around the national 7(a) portfolio, but the CDFI segment addressed throughout this article series warrants a separate consideration given its distinct scale and mission. CDFI industry assets have grown to over $446 billion as of mid-2025, and CDFI lending is disproportionately concentrated among minority-owned, women-owned, and low-income-area borrowers whose businesses, per the small-business employment statistics in Section 1, are already a significant share of the small-business population this article's aggregate model addresses. A CDFI-specific extension of this article's model would require CDFI-specific default-rate and lending-volume data comparable to the FY2025 SBA figures used in Section 3, which is not currently available in the same standardised, publicly reported form the SBA provides for its guaranteed-loan programs.

Despite this data gap, a directional inference is defensible: because CDFI borrowers are, by the sector's own design, more likely to be marginal, higher-risk-but-viable businesses than the broader small-business population an average lender serves, the potential value of early intervention catching a recoverable cash-flow problem before it becomes an unrecoverable default is plausibly higher per dollar lent in a CDFI portfolio than in a conventional lender's portfolio, even without the CDFI-specific data needed to quantify this difference with the same rigor as Section 5's national model. This is offered as a directional hypothesis for future research to test, not as a validated finding this article's evidence base can support on its own.

Recommendations

Three recommendations follow from this modelling exercise. First, institutions and researchers deploying AI-assisted early-intervention systems should prioritise measuring and publishing the actual default-reduction effect achieved, since this is precisely the missing empirical input that would allow this article's illustrative scenarios to be replaced with a validated, lending-specific figure. Second, any organisation citing this article's employment estimates should cite the full scenario range and stated assumptions in Table 3, not a single point estimate extracted without its supporting context, given how directly the output depends on the illustrative default-reduction assumption specifically. Third, future research should prioritise separately quantifying the credit-access-preservation effect discussed in Section 7, alongside the default-avoidance effect this article's model addresses, since the two are conceptually distinct and current published data supports rigorous modelling of only the latter.

A fourth recommendation follows from Section 9's CDFI discussion specifically: CDFIs and their funders and regulators should prioritise establishing the same kind of standardised, publicly reported default-rate and lending-volume data the SBA already provides for its guaranteed-loan programs, since the absence of comparable CDFI-sector data is precisely what prevented this article from extending its model to that segment with the same rigor applied to the national 7(a) portfolio. Given the CDFI sector's rapid recent growth and its disproportionate concentration among the borrower populations this article's employment-effect model is ultimately most relevant to, closing this data gap would likely be among the highest-value single steps available for strengthening the evidence base this entire article series depends on.

Conclusion

Small businesses' outsized role in U.S. employment: 45.9% of private-sector jobs and 88.9% of recent net job growth means that even a modest, credible reduction in small-business loan defaults carries a real, if currently only illustratively quantifiable, employment effect. This article's model, built transparently from FY2025 SBA lending volume and Brown and Earle's peer-reviewed employment multiplier, estimates that a conservative 10% reduction in 7(a) default rates could preserve approximately 583 jobs annually, rising to roughly 1,748 jobs under a more optimistic 30% reduction scenario. These figures are offered as a rigorous, assumption-explicit starting point for a conversation the published literature has not yet had directly what AI-assisted early intervention in small-business lending is actually worth in employment terms rather than as a final, validated answer to that question, which awaits the direct empirical measurement this article's limitations section identifies as the field's most valuable next research step. This article closes the series it belongs to by turning from architecture, governance, and validation toward the question those preceding articles ultimately serve: what difference does any of this make in the real economy. The answer this article's model offers is necessarily provisional, bounded by the honest limitations documented in Section 8. Still, it is provisional in a specific, useful way — every assumption is stated, every calculation is shown, and every figure traces back to a cited, independently verifiable source. That transparency, more than any single point estimate this article produces, is the contribution a reader should take from it: a framework ready to be populated with real deployment data the moment the field produces it, rather than a claim asking to be taken on faith in the meantime.

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