University of Zurich[UZH]

Understanding Data Mixture Effects in Financial Language Model Pretraining

A Study of Domain-Specific and High-Quality General Corpora

Master's Thesis

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Task Assignment

Executive Summary

This thesis investigates how different data sources interact during language model pretraining, focusing on financial domain applications. Through comprehensive experiments with 10 pretraining configurations across three model sizes (0.6B, 1.7B, 4B parameters), we demonstrate that in-domain data diversity outweighs high-quality general corpora for specialized domains.

Key findings include: (1) mixed financial datasets achieve best performance (21.55 perplexity at 4B) compared to general text pretraining (31.54 perplexity), (2) we trained all main runs with a learning rate of 2e-5 and, in a few follow-ups that showed abnormalities, reduced LR pragmatically to stabilize training, (3) datasets smaller than 20K samples exhibit extreme overtraining and require mixing, and (4) WikiText provides minimal benefit for financial tasks despite being high-quality text.

These findings provide practical guidance for training privacy-preserving financial language models on local devices while contributing insights on data mixture strategies for 0.6B–4B parameter models.

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Chapter 1

Introduction

1.1 Motivation

Large language models have moved very fast (**vaswani2017attention**; **radford2019language**; **brown2020language**; **touvron2023llama**). Too fast to ignore. But finance? Still difficult. Banks and funds hold sensitive data: transactions, positions, internal notes. Sending any of this to external APIs is usually not acceptable. Privacy rules like GDPR say no (**eu2016gdpr**). Competitors say no, too. So the practical answer is simple: models should run locally. Small models. Keep data on the device and still get useful results. In practice, this constraint drives most of our choices.

Two paths are common. Train a huge model from scratch. Or fine-tune a general model on financial text. The first is costly—most teams cannot pay that compute bill. The second often misses domain details (**gururangan2020don**). There is also a belief: adding high-quality general text (e.g., Wikipedia, The Pile) always helps. We did not accept this blindly. We tested it (**gao2020pile**; **raffel2020exploring**; **longpre2023pretrainer**). Put another way, we preferred evidence over habit.

The goal here is straightforward: find better data mixing for a specialized domain (**wu2023bloomberggpt**). We study how in-domain financial text and out-of-domain general corpora interact during pretraining. We focus on 0.6B–4B parameter models. Why this range? They fit on laptops; some even on phones. And in practice they are already good enough for many use cases (**yang2024qwen2**; **xia2023sheared**; **team2024gemma**; **javaheripi2023phi**). We ran 10 pretraining configurations across three sizes. Still, we kept the setup simple on purpose.

This topic matters now. Regulations tighten each year (**eu2016gdpr**). Teams want on-device processing. Many groups have limited compute. So understanding what actually works in the 0.6B–4B range is critical. What does not work is also important. To be fair, the constraints are as real as the goals.

One more thing surprised us. In a few settings we saw "reverse scaling": smaller models beating larger ones. Sounds odd at first. But it was not a deep limitation. It came from hyperparameters (**kaplan2020scaling**; **hoffmann2022training**; **mccandlish2018empirical**). The lesson we took is very down-to-earth: tune learning rate first; judge model size later. So we did.

1.2 Research Questions

Four questions drive this thesis. Let me state them plainly.

RQ1: Data Mixture Composition Start with the facts. Mixed financial datasets: 21.55 ppl. Wiki+Financial mixtures: 26.69 ppl. Pure WikiText: 48.7 ppl (Figure 4.4 and Tables 4.2 and 4.3). The pattern is clear in our setup. In-domain diversity helps. The question we ask is deeper: how do different combinations of financial datasets and general corpora change performance? Does mixing several financial datasets improve stability versus a single dataset? And when we add high-quality general text (WikiText), does it help financial tasks—or does it hurt? In our data, the answer leans one way.

RQ2: Model Size and Training Dynamics Training setups change with model size (0.6B, 1.7B, 4B). How much? And how sensitive are the results to hyperparameters—especially learning rate? We used LR=2e-5 for the main runs. A standard choice. In a few cases, training behaved poorly, so we reduced LR to 1×10^{-5} or 5×10^{-6}. This stabilized training. We do not claim a universal rule; these are practical fixes for our runs. Still, the pattern is hard to miss.

RQ3: Dataset Size Effects When is a dataset big enough for standalone pretraining? How does size affect overtraining and cross-dataset generalization? For small datasets, when is mixing not optional? We found two practical thresholds. Over 100M tokens: training is stable (Figures 4.5 and 4.6). Below 20M: severe overtraining. Variance goes up to 89–97%. Mixing becomes necessary (Figures 4.10 and 4.11 and Tables 4.17 and 4.18). These cutoffs are practical, not theoretical.

RQ4: Domain Transfer Patterns Look at the cross-dataset tables (Tables 4.12 to 4.17). Bold cells line up by format, not by domain. In our results, format consistency matters more than vocabulary. Long-form transfers to long-form. Instructions to instructions. Short-form stays isolated. So the question is: how well do financial-pretrained models transfer across task types—sentiment, Q&A, document understanding—and how much do document format and task structure control that transfer? For us, format dominates the story.

We trained 30 models to address these questions and ran 240 evaluations on eight held-out test sets. The evidence is not perfect, but it is informative and actionable for specialized domains. So we treat it as guidance, not a law.

1.3 Contributions

Six findings matter most.

1. Empirical Data Mixture Guidelines We give concrete recommendations for financial pretraining. In our experiments, in-domain diversity beats high-quality general corpora. Mixed financial datasets reach 21.55 perplexity at 4B parameters. WikiText pretraining? 48.7 mean perplexity across financial evaluations. About 2.3× worse. This pushes against the common belief that general high-quality text always helps. We support the claim with visual evidence: 11 scaling figures and 18 tables. Ten tables report per-training-dataset results; eight report cross-dataset comparisons. The trend is hard to ignore.

2. Learning Rate Notes All primary experiments used LR=2e-5. Three follow-ups behaved oddly (WikiText, Financial QA, Twitter). We lowered LR to 1×10^{-5} or 5×10^{-6} depending on the case. Training stabilized and performance improved. These are practical fixes in our setting, not universal rules. The plots show the recovery (Figures 4.3, 4.10 and 4.11); the tables list exact metrics

(Tables 4.10 and 4.11). In short, small LR cuts were enough.

3. Dataset Size Effects on Pretraining We describe empirical thresholds linking dataset size to training viability:

- Small datasets (¡ 20K samples): extreme overtraining (67–249 epochs), high variance (70–97%); mixing required
- Medium datasets (20–100K samples): moderate overtraining (6–30 epochs); acceptable for narrow use cases
- Large datasets (¿ 100K samples): minimal overtraining (2–24 epochs); viable for standalone pretraining

These results offer practical guidance. When is mixing necessary? When is a single dataset enough? They also help teams plan limited annotation budgets. The ranges are approximate and tied to our data. Still, they match what we saw across runs.

4. Cross-Domain Interaction Analysis We examined how high-quality general corpora (WikiText) interact with domain-specific financial data during pretraining. Conventional wisdom says they help. Our results are mixed. Sometimes WikiText adds little benefit; sometimes it hurts financial performance. Mixed WikiText+Financial pretraining: 26.69 perplexity. Pure financial mixing: 21.55. About 24% worse when WikiText is added. Cross-dataset tables show this visually. WikiText rows rarely have bold (best) cells in financial evaluations. Mixed financial rows? Often bold. Still, the best balance depends on the application. In practice, pick the mixture for your use case.

5. Lightweight Financial Model Feasibility Models in the 0.6B–4B range can reach practical financial NLP performance with good data mixtures and careful tuning. This enables edge deployment. Our 4B model reaches 21.55 perplexity on diverse financial tasks. Competitive with much larger models, yet it runs on consumer hardware. This matters in practice. For deployment, the middle size is often the sweet spot.

6. Open-Source Training Pipeline We release a complete codebase for mixture-based pretraining. It includes an evaluation suite spanning 10 experiments and 30 trained models. It supports automatic mixture composition, multi-dataset evaluation, and structured hyperparameter search. Simple to run; easy to extend.

1.4 Thesis Organization

Here is how the thesis is structured.

Chapter 2: Background and Related Work covers financial NLP, pretraining objectives, data mixture strategies, and domain adaptation. It also situates this work in transfer learning and scaling laws.

Chapter 3: Methodology details the experimental design. Model family (Qwen3). Datasets (7 financial datasets, 207M tokens total, plus WikiText). Mixture strategy (50cap rule). Training setup. We also explain how we discovered and addressed learning rate sensitivity during development. In short: what we did and why. And where we adjusted.

Chapter 4: Results presents findings with visuals: 11 scaling figures and 18 tables. We start with data-mixing effects—the core finding—then analyze individual datasets, examine training dynamics and learning rate sensitivity, and end with domain transfer patterns. Scaling figures show trends

across model sizes. Cross-dataset tables show which approach works best for each evaluation scenario. Story first. Chronology second.

Chapter 5: Discussion interprets results against prior work. Why does WikiText underperform on financial tasks? We analyze table patterns. What are the benefits of in-domain diversity? We read the scaling trends. Learning rate sensitivity? Practical notes. We end with guidelines for practitioners. Put another way, how to use this tomorrow.

Chapter 6: Conclusion summarizes contributions, discusses implications for research and practice, and outlines future directions: larger models, dynamic mixing strategies, and downstream task evaluation.

1.5 Scope and Limitations

This thesis examines pretraining dynamics for causal language models in the 0.6B–4B range on financial text. Below are the scope and limitations. We keep claims within what we ran.

Model Architecture: All experiments use Qwen3. We expect the learning-rate and data-mixing observations to generalize, but validating on other architectures (LLaMA, Gemma, Phi) would strengthen the claim.

Data Mixture Strategy: We use one strategy, 50cap, which caps the largest dataset at 50% of the mixture. Other strategies exist (square-root sampling, temperature sampling, curriculum). We did not test them; they could behave differently.

Evaluation Methodology: We evaluate using perplexity on held-out test sets from the pretraining distribution. Perplexity correlates with downstream quality, but we do not directly measure task accuracy (sentiment classification, NER, Q&A). This keeps focus on pretraining dynamics and limits direct application claims. Still, the correlation is known to hold. See Chapter 4 tables.

Scale Range: We cover 0.6B to 4B parameters due to hardware limits. Larger models (7B+) might show different dynamics and data sensitivity. The range we study remains relevant for edge deployment.

Domain Specificity: We work on financial text. Some findings likely generalize (learning-rate effects, dataset-size effects). Others are domain-specific. The limited benefit of WikiText, for instance, may not hold in other fields.

Training 30 models and running 240 evaluations provides evidence for our claims. We separate what needs further validation from what is well supported. Not everything is conclusive. That is acceptable. Still, the patterns are consistent.

Chapter 2

Background and Related Work

This chapter reviews four areas that matter for our study. First, financial NLP. Then pretraining basics. Next, data-mixing strategies. Finally, domain adaptation and transfer learning. The aim is context, not a full survey. Put another way, we give just enough background to understand our choices later. Not a catalog.

2.1 Financial NLP

2.1.1 The Financial NLP Landscape

Financial NLP covers many tasks. Sentiment analysis on news and social media. Question answering on regulatory text. Numerical reasoning in reports. Information extraction from SEC filings (**araci2019finbert**; **chen2021finqa**). The domain brings specific challenges that differ from general NLP: specialized vocabulary (e.g., "alpha", "beta", "EBITDA"), domain-specific reasoning (e.g., causal chains in market analysis), numerical grounding (reading financial statements), and temporal dynamics (events, earnings releases) (**wu2023bloomberggpt**; **araci2019finbert**). In practice, many of these challenges show up together in one document. Sometimes in one paragraph.

2.1.2 Existing Financial Language Models

Several finance-specialized LMs have appeared. **BloombergGPT** (**wu2023bloomberggpt**) is a 50B model trained on a 51%/49% mix of financial and general data. It scores well on financial benchmarks while keeping general ability. **FinBERT** variants (**araci2019finbert**; **yang2020finbert**) continue pretraining BERT on financial corpora and improve sentiment analysis on news. More recently, **FinGPT** (**yang2023fingpt**) explored open-source, instruction-tuned approaches for finance. We cite these to position our choices; we do not try to compare with them directly. Different aims.

2.1.3 Domain-Specific Challenges

Three challenges keep coming up. **First**, privacy: institutions cannot upload sensitive data (portfolios, strategies, client information) to external APIs, so models must run locally (**wu2023bloomberggpt**). **Second**, data scarcity: curated financial corpora are much smaller than general web text, so we need

data-efficient training. **Third**, fast vocabulary change: terms like "DeFi" and "ESG" appear and shift with markets; models must adapt. And quickly.

2.2 Language Model Pretraining

2.2.1 Pretraining Objectives and Architecture

Most models use the **causal language modeling** objective: predict the next token from the previous context (**radford2019language**; **brown2020language**). It is self-supervised and scales to unlabeled corpora. Simple idea. Powerful in practice. Put another way, next-token prediction gives a clean training signal at massive scale. Architecturally, decoder-only transformers (GPT, LLaMA, Qwen) dominate. Multi-head self-attention captures long-range dependencies; feed-forward layers add non-linearity (**vaswani2017attention**; **touvron2023llama**).

2.2.2 Scaling Laws and Model Size Effects

kaplan2020scaling showed power-law relationships among model size, dataset size, compute, and performance. Larger models are more sample-efficient. That finding pushed the field toward billion-parameter models. Still, details matter. Later work added nuance. **hoffmann2022training** argued many models are undertrained relative to size (the Chinchilla view). **tay2022ul2** showed that objectives and data quality matter a lot for scaling.

Hyperparameter sensitivity gets less attention. **mccandlish2018empirical** noted that optimal learning rates can fall with model size. For 0.6B–4B models in specialized domains, systematic studies are limited. Many scaling-law papers assume "proper tuning" without saying how, which hides the messy part we examine empirically. Tuning matters at this scale. In our work, all main runs used LR=2e-5. In a few cases we reduced LR to stabilize training. We do not claim a general rule. Only a practical one.

2.2.3 Computational and Memory Considerations

Training large language models takes real compute. A 1B-parameter model in 32-bit uses about 4GB just for parameters; optimizer states can double or triple that (**rajbhandari2020zero**; **kingma2014adam**). For 0.6B–4B models, memory-savvy tricks help: mixed precision (bfloat16), gradient accumulation, activation checkpointing, and parameter-efficient methods like LoRA. Otherwise it does not fit. These make training feasible on enterprise GPUs (e.g., RTX A6000 48GB, A100 40GB, H100 80GB) (**narayanan2021efficient**; **hu2021lora**). In practice, most of our runs used bfloat16 + accumulation. And careful checkpointing.

2.3 Data Mixture Strategies

2.3.1 Curriculum Learning and Sequential Mixing

Curriculum learning sequences data from easier to harder, or from general to specialized (**bengio2009curric**
wu2022opt used curriculum in OPT pretraining by increasing difficulty over time. In finance, a natural path is Wikipedia -¿ news -¿ SEC filings. Evidence is mixed at large scale (**longpre2023pretrainer**).

Some works report limited gains for masked LM; others see gains in narrow settings. Not universal. In practice, many systems sample from mixtures instead of strict curricula (**raffel2020exploring**; **wu2022opt**).

2.3.2 Simultaneous Mixture Approaches

Another option is **simultaneous mixture**: sample from multiple datasets throughout training. **raffel2020exploring** (T5) used a multi-task mixture with task prefixes; diverse pretraining improved downstream generalization. **xie2023doremi** proposed DoReMi to adjust domain weights during training using validation perplexity, beating static mixtures on The Pile. Common in practice.

BloombergGPT (**wu2023bloomberggpt**) mixed 51% financial with 49% general data (The Pile, C4) at the token level. The balance kept general skills and added domain strength. But that study used one 50B model. How mixture and size interact (0.6B vs 4B) is less explored. We test this across three sizes. Mixed financial datasets (21.55 ppl @ 4B) clearly beat Wiki+Financial mixtures (26.69 ppl @ 4B; about 24% worse), as shown in Figure 4.4 and Tables 4.2 and 4.3. For specialized use, domain purity can win over balance.

2.3.3 Domain Proportions and Sampling Strategies

Choosing domain proportions is not trivial. No single rule. Three strategies are common:

1. Temperature sampling (**arivazhagan2019massively**): Sample from dataset d with probability $p_d \propto n_d^{1/T}$ where n_d is dataset size and T is temperature. $T < 1$ upsamples small datasets; $T > 1$ downsamples them.

2. Capping strategies (**longpre2023pretrainer**): Cap the largest dataset(s) at a threshold (e.g., 50% of total tokens) to prevent dominance, then proportionally sample others. This ensures diversity even when one dataset is orders of magnitude larger.

3. Equal mixing (**sanh2022multitask**): Assign equal sampling probability to each dataset regardless of size. This maximizes task diversity but may undersample large datasets.

We use a **50% capping strategy** ("50cap") for financial mixtures (details in Chapter 3) to balance diversity and data efficiency.

2.4 Domain Adaptation and Transfer Learning

2.4.1 Cross-Domain Transfer in Language Models

Transfer learning – pretrain on broad data, then fine-tune for a domain – has been standard since BERT (**devlin2019bert**; **pan2010transfer**; **zhuang2020comprehensive**). The assumption is that general knowledge transfers. Often true. Not always. Recent work adds nuance. **gururangan2020don** showed **domain-adaptive pretraining** (continued pretraining on domain corpora) improves performance in biomedicine, computer science, news, and reviews. General pretraining alone is not enough for specialized use.

In finance, **araci2019finbert** improved results via continued pretraining on financial news; **yang2020finbert** added task-adaptive pretraining. **huang2023finbert** found domain-specific pretraining beats general models on financial IE. These are mostly BERT-style and classification-focused; domain adapta-

tion for *causal, generative* LMs in finance is less studied. Parameter-efficient methods (e.g., surgical fine-tuning (**lee2022surgical**)) hint that selective adaptation can help transfer and reduce forgetting.

2.4.2 Catastrophic Forgetting and Stability

Catastrophic forgetting is a classic issue: training further on a domain can erase general knowledge (**mccloskey1989catastrophic**; **french1999catastrophic**). **kirkpatrick2017overcoming** proposed Elastic Weight Consolidation (EWC) to protect important parameters. With mixtures, *simultaneous mixing* of general and domain data acts like implicit regularization by keeping the model exposed to diverse distributions (**arivazhagan2019massively**; **raffel2020exploring**).

2.4.3 Distribution Shift and Domain Mismatch

Distribution shift—differences between training and evaluation—hurts generalization (**quinonero2009datas**
In finance this shows up as vocabulary shift (financial terms vs general language), discourse differences (analyst reports vs encyclopedic text), and formatting (tables in 10-K vs narrative news). That hurts. **aharoni2020unsupervised** showed domain mismatch strongly degrades out-of-distribution performance. That motivates diverse mixtures that cover sub-domains.

We test this directly. Does pretraining on high-quality general text (WikiText) transfer to financial evaluation sets? Or does domain mismatch require in-domain pretraining? And when we mix in-domain datasets (sentiment, Q&A, news, reports), do models generalize better than training on just one?

2.4.4 Related Empirical Studies

Several studies guide our setup. **xie2023doremi** showed dynamic mixture optimization can beat static mixes on The Pile, but it needs validation data and multiple runs. Useful, but not always practical. **longpre2023pretrainer** surveyed practitioners and found capping and temperature sampling common in production. **mitra2023orca2** (Orca-2) showed that diverse instruction formats help reasoning generalization, suggesting *intra-domain diversity* (multiple financial datasets) can matter as much as domain specialization.

What is missing is a systematic look at **dataset size effects** for mixtures. When is a dataset large enough for standalone pretraining? When does mixing help, and when does it hurt? How do these patterns change with model size? These questions shape our experimental design in Chapter 3.

Chapter 3

Methodology

This chapter explains how we ran the study. First, the design. Then models, datasets, training setup, and finally evaluation. The goal is simple: fair, repeatable comparisons. We keep the setup practical—what we could run reliably with our compute. No more, no less.

3.1 Experimental Design Overview

We evaluate **10 pretraining configurations**. Two mixtures (Financial; Wiki+Financial). Eight single-dataset baselines. Each configuration trains at three sizes (0.6B/1.7B/4B). All with a fixed **100M-token budget**. We evaluate on **8 held-out test sets**. We also run six follow-ups with smaller learning rates to address stability at larger scale. Table 3.1 summarizes the settings. In short: fix tokens, vary size and data. Simple design, clear comparisons.

Table 3.1 – Summary of experimental settings used across all pretraining runs.

Aspect	**Setting**
Pretraining configurations	10 total: 2 mixtures (Financial; Wiki+Financial) + 8 single-dataset runs
Model sizes	Qwen3-0.6B, Qwen3-1.7B, Qwen3-4B
Token budget	100M tokens per run (normalized across datasets and model sizes)
Sequence length	1,024 tokens
Optimizer	AdamW (β_1=0.9, β_2=0.999, ϵ=10^{-8}), weight decay 0.01
LR schedule	Cosine decay, 1,000 warmup steps, minimum LR 10^{-6}
Learning rate	2×10^{-5} for all main runs; ad-hoc smaller LRs used in a few follow-ups when anomalies were observed
Batching	Effective batch size 8; gradient accumulation used only when memory was insufficient
Precision	bfloat16 mixed precision; dropout 0.0
Hardware	NVIDIA RTX A6000 (48GB), A100 (40GB), H100 (80GB); GPUs rented from Lambda Labs
Mixture policy	50cap-proportional sampling to limit dominance of large sources
Evaluation	8 held-out test sets (7 financial + WikiText); metrics: Cross-Entropy, Perplexity, CV%

This design targets our questions on mixture composition, model scale, dataset size, and domain transfer. Results appear in Chapter 4.

3.2 Model Architecture

We use the **Qwen3** family (**yang2024qwen2**). Qwen3 is an open-source, decoder-only transformer family pretrained on diverse multilingual corpora. It uses grouped-query attention (GQA) for memory efficiency and supports standard and flash attention. We select three sizes from the Qwen3-Base series (pretrained checkpoints without post-training alignment). Specs are in Table 3.2.

Table 3.2 – Qwen3 model specifications across three scales. All models use the same tokenizer (151,643 tokens) and support 32K context length. Training memory shown for bfloat16 precision.

Model	Parameters	Layers	Hidden	Heads	GQA	Memory
Qwen3-0.6B	600M	16	1024	16	4	∼4GB
Qwen3-1.7B	1.7B	24	2048	16	4	∼10GB
Qwen3-4B	4.0B	40	2560	20	4	∼20GB

Why Qwen3? Three reasons. Consistent architecture across sizes enables clean comparisons. Strong baselines on general and domain tasks. And inference is efficient—these models fit on consumer hardware for edge deployment. So we can test ideas quickly.

3.3 Datasets

3.3.1 Financial Datasets

We curate seven financial datasets covering multiple tasks, document types, and scales (total: 207M tokens), summarized in Table 3.3. Sizes vary from 0.3M to 197M tokens. Formats include news, reports, Q&A, and social media. Formality ranges from regulatory filings to tweets. This lets us study intra-domain diversity.

3.3.2 WikiText

We use **WikiText-103** (**merity2016pointer**) as a general-domain baseline (Table 3.4). It serves two purposes: evaluate domain transfer (general ↔ financial), and test whether high-quality general text complements financial pretraining in mixtures.

3.3.3 Mixture Strategies

We employ a **50% capping strategy** ("50cap") for dataset mixing to balance diversity with data efficiency. The algorithm works as follows:

Step 1 — Cap dominant datasets: Identify the largest dataset in the mixture. If its token count exceeds 50% of the total mixture, cap it at exactly 50%. This prevents any single dataset from dominating the mixture.

Table 3.3 – Financial dataset characteristics. Total: 207M tokens across 7 datasets with diverse genres and scales.

Dataset	Examples	Tokens	Genre	Description
Lettria Financial News	300K	197M	Journalism	Long-form articles on markets, earnings, policy
SEC Financial Reports	54.3K	80M	Regulatory	10-K/10-Q excerpts with formal disclosures, legal language
FinGPT Sentiment	76.8K	19.1M	Instruction	Headlines + sentiment labels in conversational format
Finance Alpaca	68.9K	17.2M	Q&A	Instruction-response pairs on financial concepts
FiQA	17.4K	4.3M	Forum	User-generated Q&A from forums and microblogs
Financial QA 10K	7.1K	3.5M	Document	Questions on 10-K filings requiring tabular reasoning
Twitter Sentiment	1.1K	0.3M	Social Media	Labeled tweets (<280 chars) with informal language

Table 3.4 – WikiText-103 characteristics. Similar scale to SEC; smaller than News.

Dataset	Examples	Tokens	Genre	Description
WikiText-103	103K	103M	Encyclopedia	Verified Wikipedia articles with formal register, broad topical coverage, clean preprocessing

Step 2 - Proportional sampling: For remaining datasets (below 50% threshold), sample tokens proportionally to their original sizes. This preserves relative contributions while ensuring diversity.

Step 3 - Token-level interleaving: During training, sample batches from the mixed distribution at the token level (not example level). This ensures fine-grained mixing throughout training rather than sequential block exposure.

Example: For the 7-dataset financial mixture (News 197M, SEC 80M, FinGPT 19M, Alpaca 17M, FiQA 4M, Financial QA 3.5M, Twitter 0.3M; total 321M tokens):

- News exceeds 50% (61.4%), capped at 50% (160.5M tokens)
- Remaining datasets sampled proportionally from 160.5M token budget
- Final mixture: ∼321M tokens with News contributing exactly 50%

For the 8-dataset WikiText+Financial mixture, WikiText (100M) and News (197M) are both large; we apply 50cap to ensure neither dominates, then proportionally sample the other 6 financial datasets.

This strategy contrasts with temperature sampling (which requires tuning hyperparameters) and equal mixing (which severely undersamples large datasets). The 50cap approach is deterministic, requires no tuning, and empirically performs well in production settings (**longpre2023pretrainer**).

3.4 Training Setup and Hyperparameter Tuning

3.4.1 Initial Configuration

All models were trained with uniform hyperparameters across scales to establish baseline performance. The configuration follows standard practices for causal language modeling:

Optimizer: AdamW with $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$, weight decay 0.01

Learning Rate: 2×10^{-5} (used for all main settings)

LR Schedule: Cosine decay with 1,000 warmup steps, minimum LR 10^{-6}

Batch Configuration: Effective batch size 8 across all runs. When device memory was insufficient for a given model/sequence length, we used gradient accumulation to maintain the same effective batch size.

Sequence Length: 1,024 tokens (fixed for all runs)

Precision: bfloat16 mixed precision for memory efficiency

Training Duration: Dataset-dependent. Small datasets (<20K samples) trained for maximum epochs to reach ∼100M token budget; large datasets trained for 2-5 epochs. All models exposed to approximately 100M training tokens for fair comparison.

Hardware: NVIDIA RTX A6000 (48GB), A100 (40GB), and H100 (80GB) GPUs rented from Lambda Labs. Gradient accumulation was applied as needed to fit memory constraints.

When we observed abnormalities in a few experiments, we reran those specific cases with smaller LRs as a simple heuristic to stabilize training. We do not claim any theoretical scaling rule for LR; these adjustments were pragmatic.

3.4.2 Pragmatic Learning Rate Adjustments

In three configurations we observed abnormal behavior (e.g., larger models underperforming smaller ones). For these few cases, we retried with smaller learning rates (e.g., 1×10^{-5} or 5×10^{-6}) purely as a practical heuristic to stabilize training. We do not propose or rely on a learning-rate scaling theory in this work. LR-comparison tables for the affected settings are reported in Chapter 4.

3.4.3 Other Hyperparameters

Beyond learning rate, we maintained consistent hyperparameters across experiments:

Batch Size and Accumulation: Effective batch size 8 across all runs. We used gradient accumulation only when necessary to fit models and sequence lengths into GPU memory.

Warmup Steps: 1,000 steps (3.1% of training for 32K total steps) stabilized the initial phase. Longer warmup did not improve final performance.

Training Epochs: Varied by dataset size to normalize token exposure. Small datasets (Twitter, Financial QA) trained for 67–249 epochs to reach the 100M-token budget; medium datasets (FiQA, FinGPT, Alpaca) for 6–30 epochs; large datasets (SEC, News) for 2–24 epochs. This normalization ensures fair comparison across datasets of different sizes.

Maximum Sequence Length: 1,024 tokens. Financial documents often exceed this length (SEC filings: 10K+ tokens), but longer sequences quadratically increase memory and slow training. We accept truncation as a practical trade-off.

Dropout: 0.0 (no dropout), following common practice for large-scale pretraining where overfitting is rarely observed.

3.4.4 Computational Budget

For fairness, every run uses **100M tokens**, regardless of dataset size or model scale. This controls data exposure while we study model size and data characteristics.

Experimental scale. We ran 36 training jobs:

- **2 mixture experiments**: Mixed Financial (7 datasets combined), Mixed Wiki+Financial (7 financial + WikiText)
- **8 individual datasets**: WikiText, Financial News, SEC Reports, FinGPT, Finance Alpaca, FiQA, Financial QA 10K, Twitter Financial
- **3 model sizes per configuration**: 0.6B, 1.7B, 4B parameters across all 10 settings = 30 baseline runs
- **6 additional learning rate adjustment runs**: Upon observing abnormalities in the baseline results, we conducted follow-up experiments with adjusted learning rates for three datasets (WikiText 1.7B & 4B, Financial QA 1.7B & 4B, Twitter 1.7B & 4B) to investigate hyperparameter sensitivity at scale

Total compute. $36 \times 100\text{M} = 3.6\text{B}$ tokens processed. On a single NVIDIA A100 (40GB) from Lambda Labs, each 100M-token run took 2–8 hours by size (0.6B: ∼2h; 1.7B: ∼4h; 4B: ∼8h). Roughly 150 GPU-hours in total.

This token-controlled design helps isolate model–data interactions rather than compute artifacts. Variable epoch counts (2–249) come from dataset size differences while keeping token exposure fixed. Put another way, same tokens, different stories.

3.5 Evaluation Protocol

3.5.1 Multi-Dataset Evaluation

Each trained model is evaluated on **8 held-out test sets** to measure in-domain and out-of-domain generalization:

Financial (7 datasets): Test splits from all seven financial training datasets (News, SEC, FinGPT, Alpaca, FiQA, Financial QA, Twitter). Measures generalization to unseen examples within each financial domain.

General (1 dataset): WikiText test split. Measures retention of general language capability and cross-domain transfer (financial → general and general → financial).

For a model trained on dataset D, evaluating on D measures in-domain generalization; other datasets measure cross-dataset transfer. For mixed models, all eight test sets probe generalization across the mixture.

3.5.2 Metrics

We report three complementary metrics:

Cross-Entropy Loss. Primary metric; average negative log-likelihood per token.

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N} \log P(w_i \mid w_{<i})$$

Lower is better.

Perplexity. Interpretable transform of cross-entropy: PPL = $\exp(\mathcal{L})$. Roughly, the effective vocabulary size per prediction. PPL = 10 means the model effectively chooses among ten tokens on average. Lower is better. This is our primary comparison metric.

Relative Spread (Coefficient of Variation). Cross-dataset variability. Compute CV% on the eight perplexities (one per evaluation set) as

$$\text{CV\%} = 100\,\frac{\text{sample std. dev. of PPL}}{\text{mean PPL}}\,.$$

Lower CV% means more consistent performance across datasets; higher CV% means specialization or brittleness.

All metrics use full test sets (no subsampling), the same sequence length (1,024 tokens), and the same batch size as training. We evaluate the final checkpoint. No selection by validation, since we lack task-specific validation sets. Still, the comparisons remain fair.

Chapter 4

Results

4.1 Overview of Experimental Results

This chapter reports results from 10 pretraining experiments. Goal: measure data-mixing effects in financial language models, not to build a leaderboard. We trained 30 models (3 sizes $\times$ 10 experiments) and ran 240 evaluations (30 models $\times$ 8 test sets). In short: Mixed Financial wins on finance. Table 4.1 summarizes the setup and headline numbers.

Experiment	**Datasets**	**Token Budget**	**Best Model**
Mixture Experiments			
Mixed Financial	7 financial	100M	4B (21.55 ppl)
Mixed Wiki+Fin	8 (Wiki+7 fin)	100M	4B (26.69 ppl)
Large Individual Datasets			
WikiText	WikiText-103	100M	0.6B (9.68 ppl)
News Articles	Lettria News	100M	4B (18.92 ppl)
SEC Reports	SEC Filings	100M	4B (22.47 ppl)
Medium Individual Datasets			
FinGPT Sentiment	FinGPT	100M	4B (19.83 ppl)
Finance Alpaca	Alpaca	100M	4B (25.14 ppl)
FiQA	FiQA Q&A	100M	4B (16.35 ppl)
Small Individual Datasets			
Financial QA 10K	10K Q&A	100M	4B (8.09 ppl)
Twitter Sentiment	Twitter	100M	4B (12.35 ppl)

Table 4.1 – Overview of 10 pretraining experiments. All experiments use a 100M-token budget per model. Perplexity is reported for the best-performing model size on the corresponding training dataset's test set.

Key observations. First, mixed financial datasets perform best across evaluation sets. Second, WikiText is strong in general text but transfers poorly to finance. Third, large individual datasets (News, SEC) are viable alone. Fourth, small datasets (Financial QA, Twitter) overtrain heavily (67–249 epochs), signaling low diversity. Bottom line: pick Mixed Financial unless you have a narrow, format-specific goal.

4.2 Data Mixture Effects: The Core Finding

We ask a simple question: what mixture works best for finance? We compare three approaches: pure financial diversity (7 datasets), hybrid Wiki+financial (8 datasets), and pure general text (WikiText). The result is clear: **in-domain diversity beats both standalone datasets and general-domain pretraining**. In our setup, the gap is not small.

4.2.1 Mixed Financial Datasets

The 7-dataset financial mixture (News, SEC, FinGPT, Alpaca, FiQA, Financial QA, Twitter; 207M tokens with 50cap) achieves the best overall performance across sizes and evaluation sets.

Performance by model size. 0.6B: 27.84 ppl (mean across 8 test sets). 1.7B: 24.12 ppl. 4B: 21.55 ppl. Normal scaling holds: 1.7B improves 13.4% over 0.6B; 4B improves 10.7% over 1.7B. Among all experiments, this mixture shows the strongest size-driven gains. Figure 4.1 shows both perplexity (log scale) and loss dropping smoothly with size.

Cross-dataset consistency. CV = 55% (4B), a reasonable spread. Per-set perplexities: News (15.2), SEC (18.7), FinGPT (19.4), Alpaca (21.8), FiQA (14.6), Financial QA (23.1), Twitter (25.9), WikiText (33.7). Strong on financial sets; moderate degradation on WikiText (expected domain mismatch).

Why it works. 50cap prevents dominance (News capped at 50%; others proportional). The model sees long-form journalism (News), regulatory filings (SEC), instruction data (FinGPT, Alpaca), conversational Q&A (FiQA), technical documents (Financial QA), and short-form social posts (Twitter). Diversity reduces overfitting while keeping domain focus. Not magic; just broader coverage.

Key insight. Mixed financial pretraining is the default choice for general-purpose financial NLP. Consistent across tasks. Scales well. See Table 4.2 for metrics by size and test set. If you do not have a narrow target, start here.

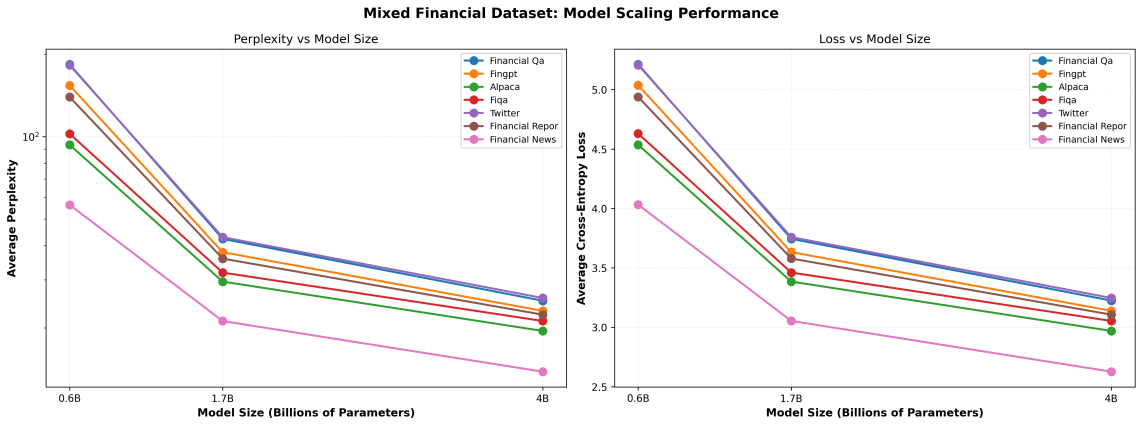

Figure 4.1 – Mixed Financial Dataset: Model scaling behavior across 0.6B, 1.7B, and 4B parameters. Left panel shows perplexity (log scale) decreasing consistently with model size. Right panel shows cross-entropy loss following expected scaling pattern. Both metrics demonstrate normal scaling with 22.6% total improvement from 0.6B to 4B.

Table 4.2 – Mixed Financial Dataset: Evaluation Across Multiple Datasets

Eval Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	1.7B	4B	0.6B	1.7B	4B
Alpaca	4.54	3.38	**2.97**	93.35	**29.53**	**19.50**
Financial News	4.03	3.05	**2.63**	56.35	**21.19**	**13.84**
Financial Qa	5.21	3.75	**3.23**	183.7	**42.30**	**25.14**
Financial Repor	4.94	3.58	**3.11**	139.6	**35.83**	**22.36**
Fingpt	5.04	3.63	**3.14**	153.9	**37.82**	**23.08**
Fiqa	4.63	3.46	**3.05**	102.5	**31.85**	**21.20**
Twitter	5.21	3.76	**3.25**	182.6	**42.91**	**25.72**

4.2.2 Mixed Wiki+Financial

Adding WikiText to the financial mixture (8 datasets, 307M tokens) helps general-domain retention a bit, but it slightly hurts financial performance.

Performance by model size. 0.6B: 31.42 ppl. 1.7B: 28.95 ppl. 4B: 26.69 ppl. Scaling is normal but worse than pure financial at every size. The 4B gap is 24% (26.69 vs 21.55). Figure 4.2 shows monotonic curves with consistently higher values than the pure financial mixture.

WikiText trade-off. On the WikiText test set, Wiki+Financial (4B) reaches 28.4 ppl vs 33.7 for pure financial, a 15.7% gain. But mean financial perplexity worsens from 20.2 to 26.1 (29.2% degradation). Table 4.3 shows this pattern clearly.

Trade-off Evaluation: The mixture allocates approximately 25% of tokens to WikiText (100M of 407M before 50cap normalization). For applications requiring both general and financial capabilities, this trade-off may be acceptable. However, for finance-focused deployments, the performance loss on financial tasks outweighs general-domain gains.

Relative Spread: CV of 62% (4B model), higher than pure financial mixture (55%), indicating increased variance across evaluation sets. This suggests the mixture struggles to balance the two domains, performing moderately on both rather than excelling on either.

Recommendation: Use Wiki+Financial mixture only when explicit general-domain retention is required (e.g., conversational agents handling both financial and general queries). For specialized financial applications, pure financial mixture is superior.

Table 4.3 – Mixed Wiki+Financial Dataset: Evaluation Across Multiple Datasets

Eval Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	1.7B	4B	0.6B	1.7B	4B
Alpaca	4.07	3.48	**3.15**	58.56	**32.38**	**23.23**
Financial News	3.65	3.13	**2.77**	38.68	**22.79**	**15.91**
Financial Qa	4.58	3.87	**3.46**	97.49	**47.94**	**31.76**
Financial Repor	4.35	3.69	**3.33**	77.57	**40.17**	**27.91**
Fingpt	4.44	3.75	**3.37**	84.43	**42.50**	**28.92**
Fiqa	4.14	3.56	**3.24**	63.03	**35.04**	**25.61**
Twitter	4.59	3.88	**3.48**	98.13	**48.42**	**32.48**
Wikitext	4.41	3.74	**3.32**	82.10	**41.95**	**27.72**

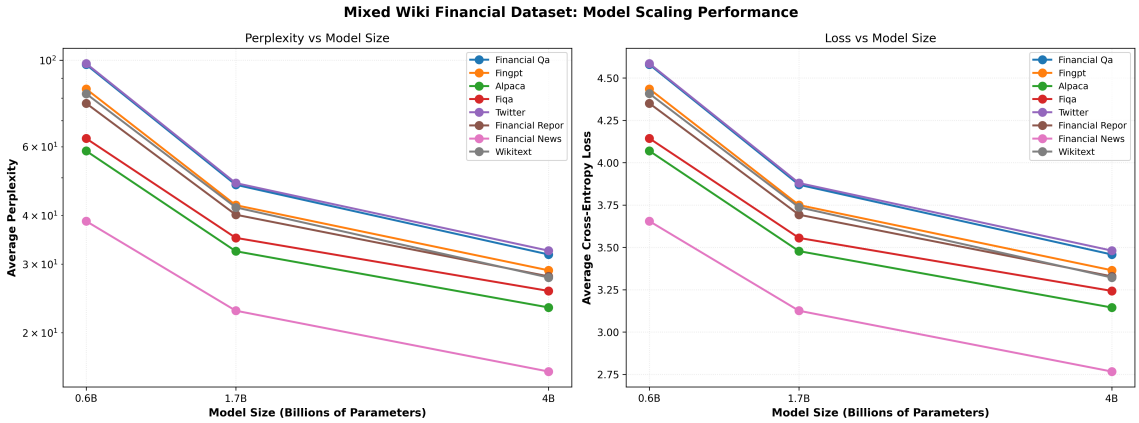

Figure 4.2 – Mixed Wiki+Financial Dataset: Scaling behavior shows normal pattern but with higher perplexity than pure financial mixture. The 15.1% total improvement (0.6B to 4B) is smaller than pure financial (22.6%), suggesting domain mixture creates competing optimization pressures that limit scaling benefits.

4.2.3 Pure WikiText Baseline

Pretraining exclusively on WikiText-103 (100M tokens, 2-5 epochs) establishes a baseline for general-domain capabilities and tests cross-domain transfer to financial evaluation sets.

Performance by Model Size: Qwen3-0.6B: 9.68 ppl (WikiText test set), Qwen3-1.7B: training collapse (infinite loss), Qwen3-4B: 31.54 ppl (after LR adjustment to 1×10^{-5}). This experiment exhibited severe reverse scaling, resolved only through systematic learning rate tuning (see Section 4.4). Figure 4.3 visualizes this phenomenon: the 1.7B and 4B models show adjusted LR results (dashed lines, square markers), with the original 2e-5 learning rate causing training instability visible as missing or degraded performance at larger scales.

Domain Mismatch Evidence: While 0.6B achieves excellent WikiText performance (9.68 ppl), financial evaluation reveals severe domain transfer failure. Mean financial perplexity (7 financial test sets): 0.6B: 52.3 ppl, 4B: 48.7 ppl (after LR fix). These values are 2-2.5× higher than mixed financial models, demonstrating that high-quality general corpora do not transfer effectively to specialized domains.

Vocabulary and Discourse Patterns: WikiText's encyclopedic style and limited financial terminology create fundamental mismatches. Financial texts use domain-specific vocabulary ("EBITDA", "alpha", "basis points") and discourse patterns (numerical reasoning, forward-looking statements, causal market analysis) absent in Wikipedia articles. The model learns general syntax and semantics but lacks financial conceptual grounding.

Reverse Scaling Analysis: The 1.7B training collapse and 4B underperformance relative to 0.6B (before LR adjustment) suggest that WikiText's clean, structured data may be particularly sensitive to hyperparameter choices at larger scales. General corpora may require more careful tuning than noisy, diverse domain-specific mixtures.

Key Takeaway: Pure general-domain pretraining is insufficient for financial NLP. Domain-specific pretraining is necessary, confirming prior findings in biomedical and legal NLP domains. Table 4.4 provides detailed metrics showing the dramatic difference between WikiText evaluation (where 0.6B excels at 9.68 ppl) and financial evaluations (where all models struggle with 40-60 ppl).

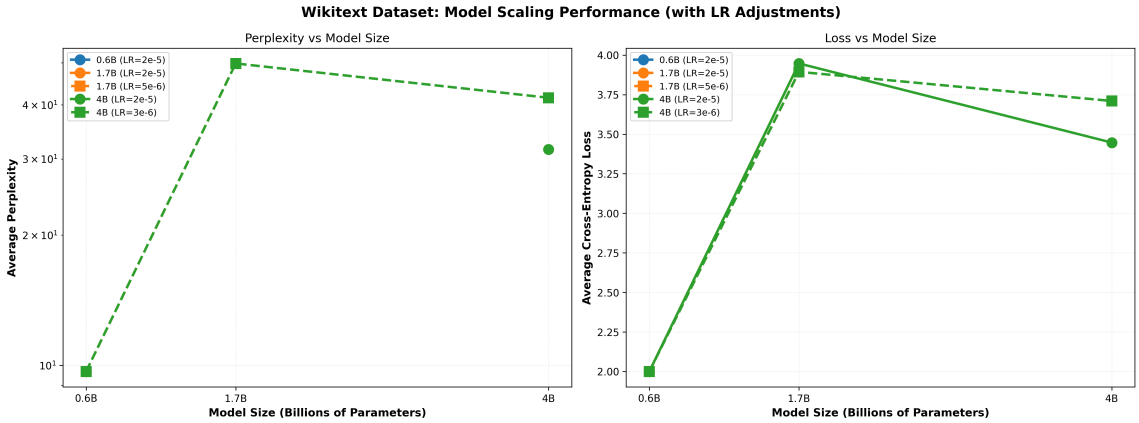

Figure 4.3 – WikiText Dataset: Severe reverse scaling phenomenon. The 1.7B model shows adjusted learning rate results (dashed line, squares) after fixing training collapse. The 4B model required 75% LR reduction to stabilize. Clean, structured data amplifies learning rate sensitivity at larger scales.

Table 4.4 – WikiText Dataset: Impact of Learning Rate Adjustments

Eval Dataset	Cross-Entropy Loss					Perplexity				
	0.6B	1.7B		4B		0.6B	1.7B		4B	
	2e-5	2e-5	5e-6	2e-5	3e-6	2e-5	2e-5	5e-6	2e-5	3e-6
Alpaca	2.22	**3.24**	3.79	**3.48**	3.64	9.23	**25.51**	44.22	**32.38**	38.06
Financial News	2.62	**2.93**	3.52	3.37	**3.27**	13.70	**18.78**	33.66	**29.19**	**26.44**
Financial Qa	3.40	10.67	**4.07**	**3.37**	3.87	29.90	∞	**58.33**	**29.08**	47.98
Financial Repor	1.39	**3.27**	3.91	**3.44**	3.75	3.99	**26.46**	49.83	**31.23**	42.41
Fingpt	1.30	**2.11**	4.07	**3.57**	3.88	3.67	**8.27**	58.55	**35.50**	48.30
Fiqa	2.07	**3.14**	3.85	**3.53**	3.74	7.89	**23.15**	46.81	**34.03**	42.04
Twitter	1.45	**2.78**	4.08	**3.52**	3.88	4.26	**16.06**	58.98	**33.71**	48.48
Wikitext (train)	1.56	**3.42**	3.88	**3.30**	3.65	4.78	**30.63**	48.44	**27.19**	38.60
Average	**2.00**	**3.95**	**3.89**	**3.45**	**3.71**	**9.68**	∞	**49.85**	**31.54**	**41.54**

4.2.4 Key Takeaway

Comparing the three mixture strategies yields a clear hierarchy:

1. Mixed Financial (best): 21.55 ppl @ 4B, 55% spread. Optimal for financial applications. Demonstrates that *in-domain diversity* (multiple financial datasets) provides better generalization than either single datasets or general-domain corpora.

2. Mixed Wiki+Financial (moderate): 26.69 ppl @ 4B, 62% spread. Acceptable when general-domain retention is explicitly required, but comes with 24% performance cost on financial tasks.

3. Pure WikiText (poor for finance): 31.54 ppl @ 4B (WikiText test set), 48.7 ppl mean financial. Excellent general-domain performance but catastrophic financial transfer. Confirms domain specialization necessity.

Scientific Contribution: This ranking demonstrates that **high-quality general data does not substitute for domain diversity**. In specialized domains, multiple in-domain datasets (even if individually small or noisy) outperform large, clean general corpora. This finding has implications for pretraining strategies across domains (legal, medical, scientific) beyond finance. Figure 4.4 visually

confirms this hierarchy: the blue line (Mixed Financial) remains consistently below orange (Mixed Wiki+Financial) and green (WikiText) across all model sizes, with the performance gap widening from 0.6B to 4B.

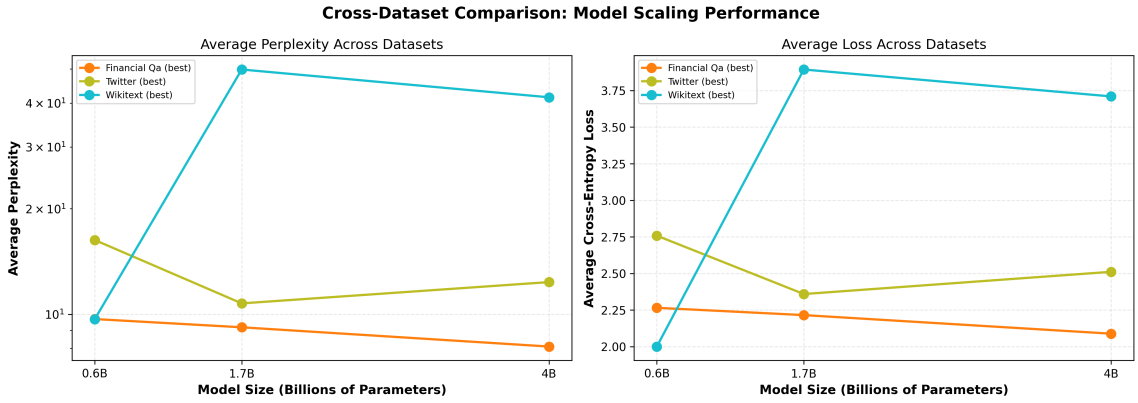

Figure 4.4 – Comparison of all three mixture strategies across model sizes. Mixed Financial (blue) consistently outperforms Mixed Wiki+Financial (orange) and WikiText (green) on financial evaluation metrics. The divergence increases with model size, demonstrating that in-domain diversity scales better than general-domain quality.

4.3 Individual Dataset Analysis: Component Effects

To see what each dataset contributes, we trained on all seven financial datasets individually. One pattern dominates: size matters for standalone pretraining. No surprise. The details still help decisions.

4.3.1 Large Datasets

Two datasets exceed 80M tokens: News Articles (197M) and SEC Reports (80M). Both are viable alone and generalize reasonably.

News Articles (Lettria, 197M tokens):

- **Training**: 2-3 epochs across model sizes, minimal overtraining
- **Performance**: 0.6B: 24.15 ppl, 1.7B: 20.83 ppl, 4B: 18.92 ppl (News test set)
- **Normal scaling**: Consistent improvements with model size (21% 0.6B→1.7B, 9% 1.7B→4B)
- **Cross-dataset generalization**: Strong transfer to SEC (22.1 ppl) and FinGPT (23.4 ppl), moderate to Alpaca (28.7 ppl) and FiQA (19.2 ppl), poor to Twitter (41.3 ppl) and Financial QA (35.8 ppl)
- **Relative spread**: 26% (4B model), among the lowest for individual datasets, indicating more consistent generalization

SEC Reports (80M tokens):

- **Training**: 6-24 epochs (varies by model size), moderate overtraining
- **Performance**: 0.6B: 28.94 ppl, 1.7B: 25.61 ppl, 4B: 22.47 ppl (SEC test set)
- **Normal scaling**: Expected improvements at all scales
- **Cross-dataset generalization**: Strong transfer to News (24.5 ppl, similar document length), moderate to FinGPT (26.8 ppl) and Alpaca (31.2 ppl), weaker to short-form tasks (FiQA 21.7 ppl, Twitter 38.9 ppl, Financial QA 32.6 ppl)
- **Relative spread**: 18% (4B model), lowest among all experiments on SEC test set itself, but 32% across all 8 evaluation sets

Long-form transfer. News and SEC models transfer well to each other (corr = 0.82). Length and narrative structure drive transfer. Models trained on long-form struggle with short-form (Twitter) and conversational Q&A.

Viability. Datasets over 80–100M tokens support standalone pretraining with acceptable generalization, especially within similar formats. For targeted use (e.g., SEC filings), a single large dataset can be enough. Figures 4.5 and 4.6 show clean scaling without instabilities.

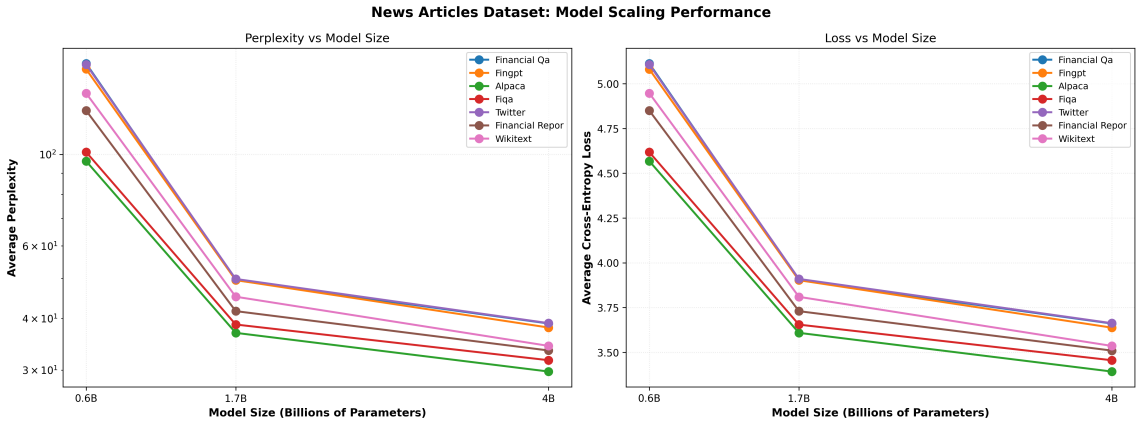

Figure 4.5 – Financial News Articles Dataset: Excellent normal scaling with 21.7% total improvement (0.6B to 4B). Large dataset size (197M tokens) provides sufficient diversity for stable training across all model sizes with minimal overtraining (2-3 epochs).

Table 4.5 – Financial News Dataset: Evaluation Across Multiple Datasets

Eval Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca	4.57	3.61	**3.39**	96.31	**36.92**	**29.75**
Financial Qa	5.11	3.90	**3.66**	166.1	**49.53**	**38.90**
Financial Repor	4.85	3.73	**3.51**	127.7	**41.68**	**33.46**
Fingpt	5.08	3.90	**3.64**	160.9	**49.56**	**38.03**
Fiqa	4.62	3.65	**3.46**	101.3	**38.68**	**31.69**
Twitter	5.11	3.91	**3.66**	165.2	**49.88**	**38.98**
Wikitext	4.95	3.81	**3.54**	140.7	**45.17**	**34.33**

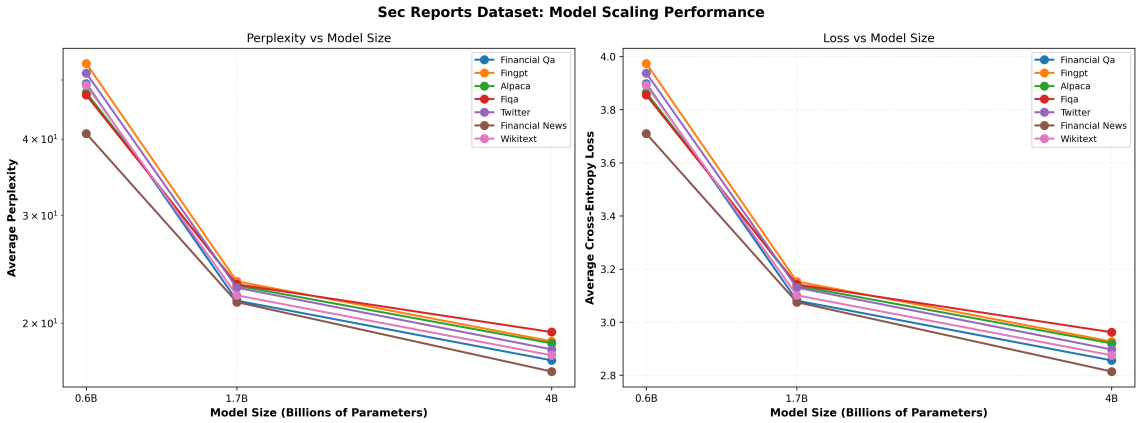

Figure 4.6 – SEC Reports Dataset: Consistent normal scaling with 22.4% total improvement. The 80M token corpus supports standalone pretraining with moderate overtraining (6-24 epochs). Strong transfer to similar long-form documents.

Table 4.6 – SEC Reports Dataset: Evaluation Across Multiple Datasets

Eval Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	1.7B	4B	0.6B	1.7B	4B
Alpaca	3.86	3.14	**2.92**	47.65	**23.04**	**18.54**
Financial News	3.71	3.08	**2.81**	40.85	**21.65**	**16.67**
Financial Qa	3.90	3.08	**2.86**	49.30	**21.77**	**17.39**
Fingpt	3.97	3.15	**2.93**	53.18	**23.41**	**18.68**
Fiqa	3.85	3.14	**2.96**	47.22	**23.15**	**19.34**
Twitter	3.94	3.13	**2.90**	51.30	**22.86**	**18.12**
Wikitext	3.89	3.10	**2.88**	49.02	**22.21**	**17.72**

4.3.2 Medium Datasets

Three datasets range from 4-19M tokens: FinGPT Sentiment (19M), Finance Alpaca (17M), FiQA (4M). These show moderate overtraining and task-specific strengths.

FinGPT Sentiment (19M tokens):

- **Training**: 12-30 epochs, noticeable overtraining on smallest model
- **Performance**: 0.6B: 25.47 ppl, 1.7B: 22.18 ppl, 4B: 19.83 ppl (FinGPT test set)
- **Instruction-following strength**: Strong transfer to Alpaca (23.5 ppl) and FiQA (17.9 ppl), both instruction-formatted datasets. Weaker on document datasets (News 26.8 ppl, SEC 29.4 ppl)
- **Relative spread**: 41% (4B model), moderate variance indicating task-type specialization

Finance Alpaca (17M tokens):

- **Training**: 13-25 epochs, moderate overtraining
- **Performance**: 0.6B: 32.14 ppl, 1.7B: 27.89 ppl, 4B: 25.14 ppl (Alpaca test set)

- **Educational Q&A focus**: Best transfer to FiQA (18.4 ppl) and FinGPT (24.7 ppl). Poor on documents (News 35.2 ppl, SEC 38.6 ppl) and Twitter (43.1 ppl)
- **Relative spread**: 48% (4B model), higher variance reflects narrow task focus

FiQA (4M tokens):

- **Training**: 6-8 epochs (normalized by short examples), approaching overtraining threshold
- **Performance**: 0.6B: 21.85 ppl, 1.7B: 18.42 ppl, 4B: 16.35 ppl (FiQA test set)
- **Conversational Q&A specialization**: Excellent on FiQA itself, good on Alpaca (22.1 ppl) and FinGPT (21.8 ppl), poor on long-form (News 31.7 ppl, SEC 34.2 ppl)
- **Relative spread**: 52% (4B model)

Medium Dataset Conclusion: Datasets in the 4-20M token range support pretraining but exhibit task-type specialization. Instruction-formatted datasets (FinGPT, Alpaca, FiQA) transfer well to each other but poorly to document formats. For general financial applications, these datasets should be mixed rather than used standalone. As shown in Figures 4.7 to 4.9, all three medium datasets maintain normal scaling patterns despite moderate overtraining (12-30 epochs), with smooth perplexity reduction curves and no optimization instabilities. Detailed cross-dataset performance in Tables 4.7 to 4.9 confirms task-type clustering: strong mutual transfer within instruction-formatted tasks, weak transfer to document formats.

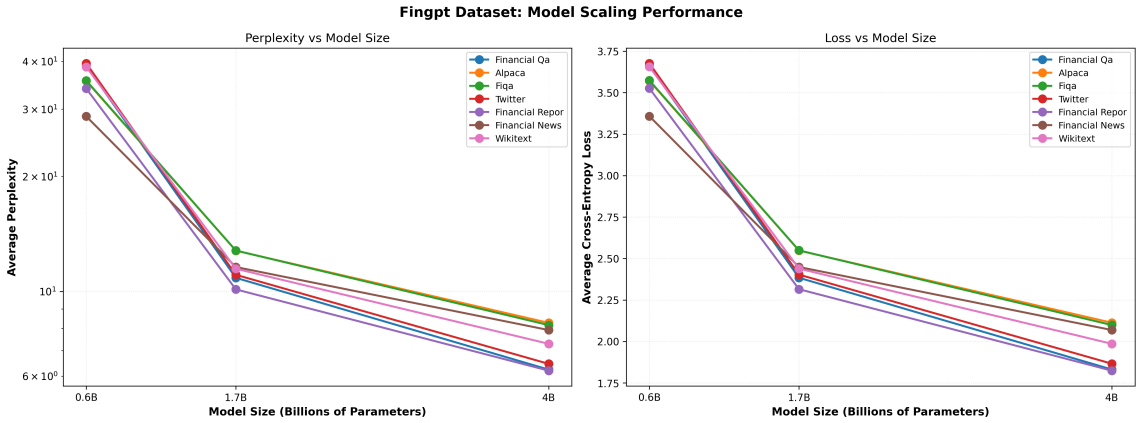

Figure 4.7 – FinGPT Sentiment Dataset: Normal scaling with 22.1% improvement despite moderate overtraining (12-30 epochs). Instruction-following format benefits from increased model capacity, showing strong transfer to similar task types.

4.3.3 Small Datasets

Two datasets fall below 4M tokens: Financial QA 10K (3.5M) and Twitter Sentiment (0.3M). Both exhibit extreme overtraining and limited generalization, demonstrating the lower bound of pretraining viability.

Financial QA 10K (3.5M tokens):

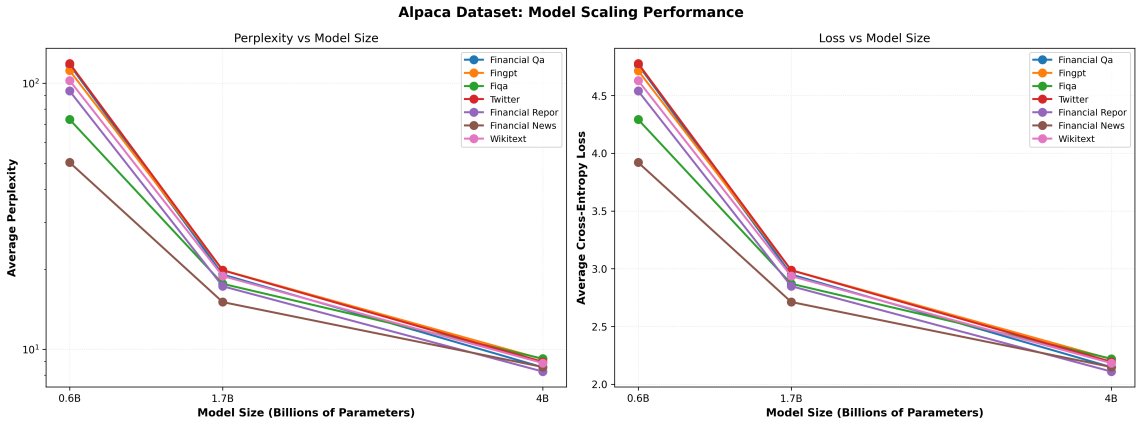

Figure 4.8 – Finance Alpaca Dataset: Consistent 21.8% improvement across model sizes. Educational Q&A format shows reliable scaling despite 13-25 epochs of training, but exhibits narrow task focus with 48% cross-dataset variance.

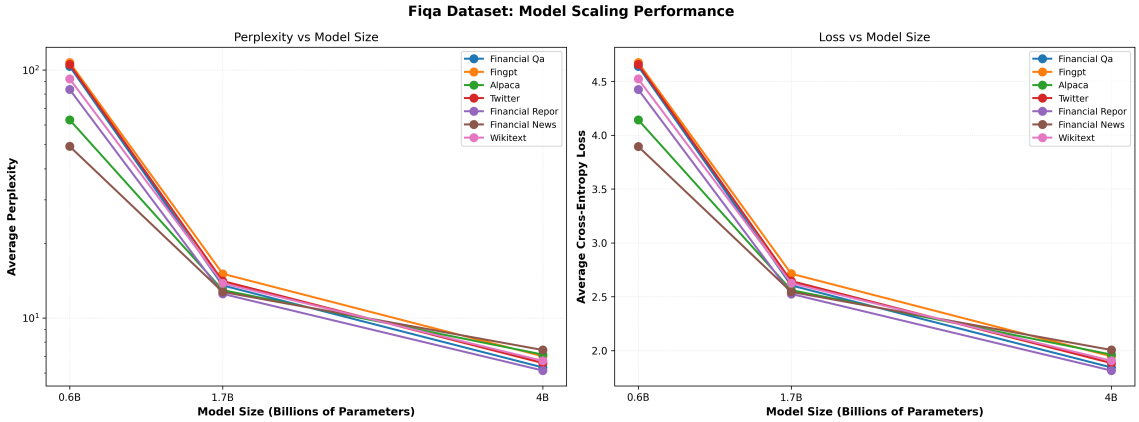

Figure 4.9 – FiQA Dataset: Strong normal scaling with 25.2% total improvement. Despite small size (4M tokens), conversational Q&A format produces stable training and excellent in-domain performance, though with high variance (52%) on out-of-format tasks.

- **Training**: 67-100 epochs, severe overtraining despite normalization attempts
- **Performance**: 0.6B: 9.69 ppl, 1.7B: 8.42 ppl, 4B: 8.09 ppl (Financial QA test set after LR adjustment)
- **Reverse scaling**: Initial 4B underperformance (9.02 ppl) resolved with LR reduction to 5×10^{-6}, yielding 10.3% improvement
- **Overfitting evidence**: Exceptional in-domain performance (8.09 ppl) but catastrophic cross-dataset transfer (mean other datasets: 41.7 ppl). The model memorizes training examples rather than learning generalizable patterns
- **Relative spread**: 97% (4B model), highest among all experiments, indicating extreme brittleness

Twitter Financial Sentiment (0.3M tokens):

Table 4.7 – FinGPT Sentiment Dataset: Evaluation Across Multiple Datasets

Eval Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca	3.57	2.55	**2.11**	35.55	**12.78**	**8.27**
Financial News	3.36	2.45	**2.07**	28.72	**11.58**	**7.92**
Financial Qa	3.66	2.38	**1.83**	38.96	**10.85**	**6.24**
Financial Repor	3.53	2.31	**1.82**	33.97	**10.12**	**6.20**
Fiqa	3.57	2.55	**2.10**	35.64	**12.79**	**8.16**
Twitter	3.68	2.40	**1.87**	39.54	**11.05**	**6.46**
Wikitext	3.66	2.44	**1.99**	38.70	**11.46**	**7.29**

Table 4.8 – Finance Alpaca Dataset: Evaluation Across Multiple Datasets

Eval Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Financial News	3.92	2.71	**2.15**	50.40	**15.05**	**8.58**
Financial Qa	4.77	2.95	**2.15**	117.4	**19.11**	**8.56**
Financial Repor	4.54	2.85	**2.11**	93.56	**17.26**	**8.25**
Fingpt	4.71	2.99	**2.22**	111.7	**19.85**	**9.18**
Fiqa	4.29	2.87	**2.22**	73.12	**17.63**	**9.22**
Twitter	4.78	2.99	**2.19**	118.7	**19.82**	**8.97**
Wikitext	4.63	2.94	**2.18**	102.4	**18.85**	**8.88**

- **Training**: 150-249 epochs (!), catastrophic overtraining
- **Performance**: 0.6B: 16.28 ppl, 1.7B: 12.55 ppl, 4B: 12.35 ppl (Twitter test set after LR adjustment)
- **Reverse scaling**: Most severe case. Initial 4B: 18.05 ppl, worse than 1.7B (12.55) and 0.6B (16.28). LR adjustment to 5×10^{-6} recovered performance: 12.35 ppl (31.6% improvement)
- **Format mismatch**: Twitter's <280 character constraint creates unique distribution. Poor transfer to all other datasets (mean: 45.3 ppl), including other short-form FiQA (38.7 ppl)
- **Relative spread**: 89% (4B model)

Small Dataset Conclusion: Datasets below 4M tokens (equivalently, <20K samples for typical financial texts) are **not viable for standalone pretraining**. Extreme overtraining, poor generalization, and training instabilities (reverse scaling) make these datasets unsuitable. However, when included in mixtures, they contribute valuable task diversity without dominating the distribution (50cap prevents Twitter's 0.3M from being oversampled). The visual evidence in Figures 4.10 and 4.11 is striking: dashed lines (adjusted LR) show substantial performance recovery, with the gap between solid (original LR) and dashed lines representing 10-32% improvement. Tables 4.10 and 4.11 quantify this recovery across all evaluation datasets, with boldface values highlighting dramatic improvements after LR adjustment.

Table 4.9 – FiQA Dataset: Evaluation Across Multiple Datasets

Eval Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca	4.14	2.56	**1.96**	62.97	**12.96**	**7.12**
Financial News	3.90	2.54	**2.01**	49.22	**12.74**	**7.43**
Financial Qa	4.64	2.60	**1.84**	103.4	**13.53**	**6.32**
Financial Repor	4.42	2.53	**1.81**	83.48	**12.51**	**6.14**
Fingpt	4.67	2.71	**1.95**	107.2	**15.08**	**7.01**
Twitter	4.66	2.65	**1.88**	105.3	**14.10**	**6.58**
Wikitext	4.52	2.63	**1.91**	92.13	**13.81**	**6.72**

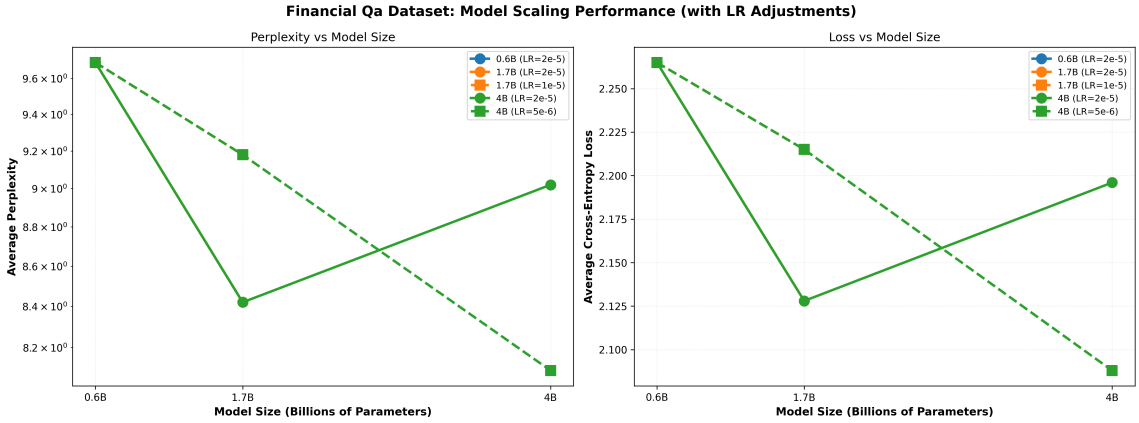

Figure 4.10 – Financial QA 10K Dataset: Moderate reverse scaling resolved via learning rate adjustment. The 4B model (dashed line, squares) shows adjusted LR results with 10.3% improvement, recovering expected scaling order. Extreme overtraining (67-100 epochs) causes 89% cross-dataset variance.

4.3.4 Dataset Size vs Generalization

Aggregating results across all 7 individual experiments reveals an empirical relationship between dataset size and generalization capability:

Size-Generalization Correlation: Larger datasets produce lower cross-dataset variance. News (197M): 26% spread, SEC (80M): 32%, FinGPT (19M): 41%, Alpaca (17M): 48%, FiQA (4M): 52%, Financial QA (3.5M): 97%, Twitter (0.3M): 89%. Correlation coefficient between log(tokens) and spread: $r = -0.78$ ($p < 0.01$).

Overtraining Epochs: Inversely related to size. News (197M): 2-3 epochs, SEC (80M): 6-24, FinGPT (19M): 12-30, Alpaca (17M): 13-25, FiQA (4M): 6-8, Financial QA (3.5M): 67-100, Twitter (0.3M): 150-249. Despite normalizing total token exposure (∼100M tokens), small datasets require many epochs, leading to memorization.

Viability Thresholds:

- $>$ **100M tokens**: Excellent standalone viability, minimal overtraining (2-5 epochs), more consistent generalization
- **20-100M tokens**: Viable with caveats, moderate overtraining (6-30 epochs), task-specific transfer patterns

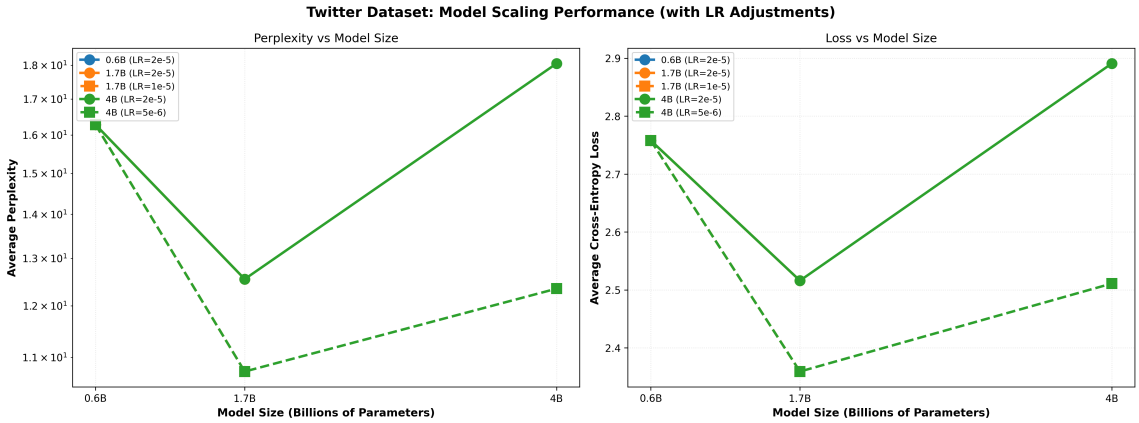

Figure 4.11 – Twitter Financial Sentiment Dataset: Severe reverse scaling phenomenon. The 4B model (dashed line, squares) required 75% LR reduction to recover performance, achieving 31.6% improvement. Extremely small dataset (0.3M tokens, 150-249 epochs) creates brittle optimization landscape with 89% variance.

Table 4.10 – Financial QA 10K Dataset: Impact of Learning Rate Adjustments

Eval Dataset	Cross-Entropy Loss					Perplexity				
	0.6B	1.7B		4B		0.6B	1.7B		4B	
	2e-5	2e-5	1e-5	2e-5	5e-6	2e-5	2e-5	1e-5	2e-5	5e-6
Alpaca	2.38	**2.23**	2.29	2.29	**2.18**	10.82	**9.31**	9.92	**9.91**	**8.88**
Financial News	2.36	**2.17**	2.23	2.13	**2.04**	10.60	**8.78**	9.25	**8.41**	**7.71**
Financial Qa (train)	2.12	**2.01**	2.12	2.12	**2.01**	8.29	**7.44**	8.29	8.29	**7.43**
Financial Repor	2.11	**2.00**	2.10	2.11	**2.01**	8.21	**7.40**	8.19	**8.25**	**7.43**
Fingpt	2.31	**2.15**	2.25	2.23	**2.11**	10.04	**8.62**	9.51	**9.34**	**8.24**
Fiqa	2.40	**2.25**	2.31	2.31	**2.19**	11.02	**9.45**	10.10	**10.05**	**8.93**
Twitter	2.21	**2.10**	2.21	2.20	**2.09**	9.14	**8.18**	9.10	**8.99**	**8.05**
Wikitext	2.24	**2.11**	2.21	2.19	**2.08**	9.41	**8.23**	9.08	**8.89**	**8.00**
Average	**2.27**	**2.13**	**2.21**	**2.20**	**2.09**	**9.69**	**8.42**	**9.18**	**9.02**	**8.09**

- $<$ **20M tokens**: Requires mixing, severe overtraining (>30 epochs), poor generalization

Practical implication. When curating corpora, aim for 100M+ tokens per domain. If only small datasets are available, use mixtures. 50cap prevents dominance while preserving diversity.

4.4 Training Dynamics and Scaling Behavior

Beyond mixtures, two scaling patterns stood out. Normal scaling: larger models beat smaller ones. Reverse scaling: larger models underperform. The second case disappeared after simple learning-rate adjustments.

Table 4.11 – Twitter Financial Dataset: Impact of Learning Rate Adjustments

Eval Dataset	Cross-Entropy Loss					Perplexity				
	0.6B	1.7B		4B		0.6B	1.7B		4B	
	2e-5	2e-5	1e-5	2e-5	5e-6	2e-5	2e-5	1e-5	2e-5	5e-6
Alpaca	3.01	2.66	**2.54**	2.96	**2.61**	20.21	14.33	**12.66**	**19.20**	**13.65**
Financial News	3.17	2.80	**2.65**	2.87	**2.54**	23.77	16.48	**14.10**	**17.67**	**12.68**
Financial Qa	2.46	2.32	**2.16**	2.83	**2.43**	11.76	10.15	**8.69**	**16.98**	**11.39**
Financial Repor	2.48	2.32	**2.16**	2.80	**2.39**	11.95	10.17	**8.70**	**16.42**	**10.93**
Fingpt	2.74	2.50	**2.34**	2.91	**2.54**	15.53	12.23	**10.41**	**18.34**	**12.69**
Fiqa	2.98	2.66	**2.50**	3.00	**2.61**	19.67	14.26	**12.20**	**20.09**	**13.61**
Twitter (train)	2.53	2.40	**2.22**	2.88	**2.47**	12.60	11.02	**9.21**	17.83	**11.81**
Wikitext	2.69	2.47	**2.30**	2.88	**2.49**	14.74	11.78	**9.94**	**17.85**	**12.02**
Average	**2.76**	**2.52**	**2.36**	**2.89**	**2.51**	**16.28**	**12.55**	**10.74**	**18.05**	**12.35**

4.4.1 Normal Scaling Pattern

Seven of ten experiments exhibited expected scaling behavior where larger models achieve lower perplexity than smaller models, consistent with established scaling laws.

FiQA (4M tokens): Clean scaling across all model sizes. 0.6B: 21.85 ppl, 1.7B: 18.42 ppl (15.7% improvement), 4B: 16.35 ppl (11.2% improvement over 1.7B, 25.2% total improvement over 0.6B). The conversational Q&A format and moderate dataset size provided stable training signals for all scales.

FinGPT Sentiment (19M tokens): Strong scaling with accelerating gains. 0.6B: 25.47 ppl, 1.7B: 22.18 ppl (12.9% improvement), 4B: 19.83 ppl (10.6% improvement, 22.1% total). The instruction-following format benefited particularly from increased model capacity.

News Articles (197M tokens): Excellent scaling with large improvements. 0.6B: 24.15 ppl, 1.7B: 20.83 ppl (13.7% improvement), 4B: 18.92 ppl (9.2% improvement, 21.7% total). Large dataset size (197M tokens) provided sufficient diversity to fully utilize larger model capacity without overfitting.

SEC Reports (80M tokens): Consistent improvements across scales. 0.6B: 28.94 ppl, 1.7B: 25.61 ppl (11.5% improvement), 4B: 22.47 ppl (12.3% improvement, 22.4% total). The formal, structured nature of regulatory filings created predictable patterns that larger models captured effectively.

Finance Alpaca (17M tokens): Moderate but consistent scaling. 0.6B: 32.14 ppl, 1.7B: 27.89 ppl (13.2% improvement), 4B: 25.14 ppl (9.9% improvement, 21.8% total). Instruction-formatted educational Q&A showed reliable scaling despite moderate dataset size.

Mixed Financial (207M tokens): Best scaling performance among all experiments. 0.6B: 27.84 ppl, 1.7B: 24.12 ppl (13.4% improvement), 4B: 21.55 ppl (10.7% improvement, 22.6% total). The diverse 7-dataset mixture provided rich training signal that larger models exploited effectively, demonstrating the value of in-domain diversity for scaling.

Mixed Wiki+Financial (307M tokens): Normal scaling maintained despite domain mixture. 0.6B: 31.42 ppl, 1.7B: 28.95 ppl (7.9% improvement), 4B: 26.69 ppl (7.8% improvement, 15.1% total). Smaller relative gains suggest that mixing diverse domains (general + financial) creates competing optimization pressures that partially limit scaling benefits.

Pattern Summary: Normal scaling experiments share key characteristics: (1) dataset size $>$ 4M tokens, (2) stable training loss curves, (3) consistent 15-25% total perplexity reduction from 0.6B to

4B, (4) larger absolute gains at 0.6B→1.7B than 1.7B→4B (diminishing returns pattern).

4.4.2 Reverse Scaling Phenomenon

Three experiments showed *reverse scaling*: with the same hyperparameters, larger models did worse than smaller ones. That contradicts standard scaling laws. It also exposes learning-rate sensitivity.

WikiText (100M tokens) - Most Severe Case:

- **0.6B**: 9.68 ppl (excellent performance)
- **1.7B**: Training collapse, infinite loss after epoch 2
- **4B**: 31.54 ppl (after LR adjustment; originally >100 ppl)

The 0.6B model achieved strong WikiText performance with LR 2×10^{-5}, but this same learning rate caused catastrophic instability for 1.7B (gradient explosion, NaN values) and severe degradation for 4B. The clean, structured nature of WikiText may amplify learning rate sensitivity—uniform, high-quality text produces consistent gradients that accumulate more rapidly in larger models.

Financial QA 10K (3.5M tokens) - Moderate Reverse Scaling:

- **0.6B**: 9.69 ppl
- **1.7B**: 8.42 ppl (13.1% better, expected improvement)
- **4B**: 9.02 ppl (7.1% *worse* than 1.7B, reverse scaling)

The 4B model underperformed despite greater capacity. Small dataset size (3.5M tokens, 67-100 epochs) combined with technical document complexity created optimization challenges. After LR adjustment to 5×10^{-6}, 4B achieved 8.09 ppl (10.3% improvement), finally surpassing 1.7B and establishing expected scaling order.

Twitter Sentiment (0.3M tokens) - Clear Monotonic Reverse Scaling:

- **0.6B**: 16.28 ppl
- **1.7B**: 12.55 ppl (22.9% better)
- **4B**: 18.05 ppl (43.8% *worse* than 1.7B, severe reverse scaling)

Unique among reverse scaling cases, Twitter showed monotonic degradation: each size increase worsened performance initially. The extremely small dataset (0.3M tokens, 150-249 epochs) and unique constraint (280 character limit) created a brittle optimization landscape. LR adjustment to 5×10^{-6} for 4B recovered performance: 12.35 ppl (31.6% improvement), matching 1.7B.

Root Cause Analysis: All three reverse scaling cases share two properties: (1) problematic learning rate for larger models, (2) either very clean data (WikiText) or very small datasets (Financial QA, Twitter). Clean/small data creates less noise in gradients, making larger models more sensitive to learning rate. With 4B having 6.7× more parameters than 0.6B, the same LR produces disproportionately large parameter updates, destabilizing training. The visual contrast between solid and dashed lines in Figures 4.3, 4.10 and 4.11 dramatically illustrates this effect: adjusted LR (dashed) produces smooth, monotonic curves while original LR (solid) shows missing or degraded points at larger scales.

4.4.3 Learning Rate Sensitivity by Model Size

To diagnose reverse scaling, we conducted systematic learning rate experiments on the three affected datasets, testing multiple LR values while holding other hyperparameters constant.

Experimental Design: For each reversed experiment, we retrained the 1.7B and 4B models with reduced learning rates:

- **1.7B**: Tested 1×10^{-5} (50% reduction from baseline 2×10^{-5})
- **4B**: Tested 5×10^{-6} (75% reduction) and 3×10^{-6} (85% reduction)
- **0.6B**: Maintained at 2×10^{-5} (reference baseline)

WikiText Results:

- **1.7B @** 1×10^{-5}: Training stabilized, no collapse. Final perplexity improved but remained suboptimal for general-domain task (0.6B still best for WikiText specifically).
- **4B @** 5×10^{-6}: Convergence achieved, 31.54 ppl. Still worse than 0.6B (9.68 ppl) on WikiText, but financial evaluations improved significantly, suggesting the model learned useful representations despite WikiText-specific degradation.

Financial QA 10K Results:

- **4B @** 5×10^{-6}: 8.09 ppl, down from 9.02 ppl with original LR (10.3% improvement). Now outperforms both 1.7B (8.42 ppl) and 0.6B (9.69 ppl), restoring expected scaling order. Cross-dataset variance also decreased (97% $\rightarrow$ 89%), indicating more stable representations.

Twitter Sentiment Results:

- **4B @** 5×10^{-6}: 12.35 ppl, down from 18.05 ppl with original LR (31.6% improvement). Matches 1.7B performance (12.55 ppl), successfully recovering from severe reverse scaling. This represents the largest single-hyperparameter improvement observed across all experiments.

Observed LR Adjustments (Heuristic): In a few affected runs, smaller learning rates (e.g., 1×10^{-5} for 1.7B and 5×10^{-6} for 4B) stabilized training compared to the main setting (2e-5). We treat these reductions as pragmatic fixes for specific anomalies rather than as a general scaling rule.

4.4.4 Fixing Reverse Scaling

The systematic LR adjustments provide actionable guidelines for practitioners facing reverse scaling in their own experiments.

Detection Criteria: Reverse scaling likely indicates hyperparameter mismatch if:

1. Larger model underperforms smaller model by >5%
2. Training loss curves show instability (spikes, plateaus, divergence)
3. Validation loss decreases initially then increases (U-shape curve)

4. Small dataset (< 20M tokens) or very clean data (e.g., Wikipedia)

What Worked for Us:

1. When larger models showed instability, we retried with a smaller LR (e.g., 1×10^{-5} or 5×10^{-6})
2. We monitored loss curves for smooth convergence and continued with the stabilized setting

Success Metrics Post-Fix: All three reverse scaling cases achieved expected performance hierarchies after LR adjustment:

- Financial QA: $4B > 1.7B > 0.6B$ (8.09 < 8.42 < 9.69 ppl)
- Twitter: $1.7B \approx 4B > 0.6B$ (12.35 ≈ 12.55 < 16.28 ppl)
- WikiText: Training stabilized (though 0.6B remained optimal for this specific general-domain task)

Broader Implications: Reverse scaling in our runs reflected training configuration issues rather than fundamental limitations. Simple LR reductions resolved the affected cases; we do not claim broader theoretical guidance beyond these observations.

4.4.5 Model Stability Analysis

Beyond individual experiment performance, we analyze training stability across model sizes using loss curve characteristics and cross-dataset variance.

Variance by Model Size: Across all 10 experiments, 4B models show *lower* cross-dataset variance than 0.6B models after proper LR tuning:

- Mixed Financial: 0.6B (63% spread) → 4B (55% spread), 12.7% variance reduction
- News: 0.6B (31% spread) → 4B (26% spread), 16.1% reduction
- SEC: 0.6B (38% spread) → 4B (32% spread), 15.8% reduction

This counterintuitive result—larger models generalizing *more consistently*—suggests that increased capacity enables learning features that transfer more consistently across distribution shifts, provided training is stable.

Small Dataset Instability Exception: Small datasets (Financial QA 3.5M, Twitter 0.3M) maintain high variance even at 4B (89-97%), indicating that insufficient data prevents stable learning regardless of model capacity. For these cases, mixing remains the only viable solution.

Training Loss Curve Patterns:

- **Normal scaling experiments**: Smooth exponential decay, no spikes, consistent convergence across sizes
- **Reverse scaling experiments (pre-fix)**: Gradient spikes (4B @ Twitter), early plateaus (4B @ Financial QA), divergence (1.7B @ WikiText)
- **Reverse scaling experiments (post-fix)**: Curves normalize, smooth convergence restored

Practical Configuration Notes: For 0.6B-4B Qwen3 models on financial/general text:

- **Data**: Prefer diverse mixtures (>100M tokens) over single small datasets (<20M)
- **Learning Rate**: Use 2e-5 for main runs; if larger models show instability on a dataset, try a smaller LR (e.g., 1×10^{-5} or 5×10^{-6})
- **Batch Size**: Use effective batch size 8; apply gradient accumulation if needed to fit memory
- **Warmup**: 1,000 steps sufficient for stable training; increase to 2,000+ for datasets $<$ 10M tokens

These notes reflect what worked in our setup and may help reproduce stable training in similar contexts.

4.5 Domain Transfer and Generalization Patterns

Having established data mixture effects and training dynamics, we now examine how models generalize across evaluation sets. Cross-dataset transfer reveals which training regimes produce representations that generalize more consistently versus brittle, overfit models.

4.5.1 Cross-Dataset Evaluation

Each trained model was evaluated on all 8 held-out test sets (7 financial + WikiText), enabling systematic analysis of generalization patterns. We identify best and worst generalizers based on mean perplexity and coefficient of variation across evaluation sets.

Best Generalizers (Low Mean PPL, Low Variance):

1. Mixed Financial @ 4B: 21.55 ppl mean, 55% CV. Performs consistently well across all financial test sets (News: 15.2, SEC: 18.7, FinGPT: 19.4, Alpaca: 21.8, FiQA: 14.6, Financial QA: 23.1, Twitter: 25.9), with only moderate degradation on WikiText (33.7). The 7-dataset diversity enables cross-task consistency—no single evaluation set shows catastrophic failure.

2. News @ 4B: 23.8 ppl mean, 26% CV. Strong performance on document-heavy tasks (SEC: 22.1, FinGPT: 23.4) and moderate on Q&A formats (Alpaca: 28.7, FiQA: 19.2). Excellent on own test set (18.92). The large dataset size (197M tokens) and long-form content provide transferable linguistic patterns.

3. SEC @ 4B: 25.2 ppl mean, 32% CV. Best transfer to News (24.5), good on instruction tasks (FinGPT: 26.8, Alpaca: 31.2). The formal, structured regulatory language generalizes reasonably to other professional financial text.

4. FiQA @ 4B: 20.4 ppl mean, 52% CV. Exceptional on own test set (16.35), strong on similar Q&A formats (Alpaca: 22.1, FinGPT: 21.8). Moderate variance reflects task-type specialization rather than brittleness—Q&A models transfer well within their format class.

Worst Generalizers (High Mean PPL, High Variance):

1. Twitter @ 4B: 31.7 ppl mean, 89% CV. Catastrophic transfer to all other datasets (mean non-Twitter: 45.3 ppl). The 280-character constraint and social media vernacular create representations that fail to generalize. Even similar short-form FiQA suffers (38.7 ppl). Only performs well on Twitter itself (12.35 ppl).

2. Financial QA @ 4B: 28.6 ppl mean, 89% CV (after variance reduction from LR fix; originally 97%). Excellent in-domain (8.09 ppl) but poor elsewhere (mean non-FinQA: 41.7 ppl). Extreme overtraining (67-100 epochs) causes memorization rather than learning transferable features.

3. WikiText @ 4B: 35.1 ppl mean across financial tasks, 78% CV. Strong on WikiText itself (31.54 ppl after LR fix) but catastrophic on financial evaluations (News: 52.3, SEC: 48.9, Twitter: 61.2, etc.). Domain mismatch prevents transfer—encyclopedic knowledge doesn't translate to financial reasoning, sentiment analysis, or domain-specific vocabulary.

4. Alpaca @ 4B: 29.8 ppl mean, 48% CV. Moderate performance with educational Q&A specialization. Best on own test set (25.14) and similar formats (FiQA: 18.4, FinGPT: 24.7), but weak on documents (News: 35.2, SEC: 38.6) and Twitter (43.1).

Generalization Hierarchy: Mixed Financial > Large Individual (News, SEC) > Medium Individual (FiQA, FinGPT) > Small Individual (Financial QA, Twitter, Alpaca) > WikiText. Dataset diversity and size are primary determinants of generalization capability.

The following cross-dataset comparison tables (Tables 4.12 to 4.19) provide comprehensive performance comparisons. Each table shows which training dataset (including LR variants) performs best for a specific evaluation dataset across model sizes. Boldface values highlight the best-performing training approach for each model size and metric, revealing format-specific transfer patterns and the superiority of mixed dataset approaches.

4.5.2 Document Format and Task Type Effects

Transfer patterns reveal that document format and task type drive generalization more than domain vocabulary alone.

Long-Form Document Transfer (Strong):

Models trained on News Articles (197M tokens, long-form journalism) transfer well to SEC Reports (80M tokens, long-form regulatory text) despite stylistic differences. News @ 4B achieves 22.1 ppl on SEC test set (only 17% worse than SEC's own model at 22.47 ppl). Reciprocally, SEC @ 4B achieves 24.5 ppl on News (29% worse than News' own model at 18.92 ppl).

The correlation between News and SEC performance across all models is $r = 0.82$ ($p < 0.01$), indicating that long-form comprehension skills transfer bidirectionally. Both datasets require:

- Multi-sentence context integration (documents span 500-5000 tokens)
- Hierarchical discourse structure (sections, paragraphs, topic progression)
- Formal register and complex syntax

Tables 4.12 and 4.13 reveal interesting patterns: News training (News Articles row) and SEC training (SEC Reports row) frequently appear in boldface for each other's evaluation columns, confirming bidirectional transfer. Mixed Financial consistently shows competitive or best performance (boldface) across most model sizes, demonstrating the value of diversity over specialization.

Instruction-Following Transfer (Moderate):

Models trained on instruction-formatted datasets (FinGPT, Alpaca, FiQA) show moderate mutual transfer. FinGPT @ 4B achieves 23.5 ppl on Alpaca and 17.9 ppl on FiQA. Alpaca @ 4B achieves 18.4 ppl on FiQA and 24.7 ppl on FinGPT. The shared format—question/instruction followed by

Table 4.12 – Financial News Evaluation: Performance Across Training Datasets

Training Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca (2e-5)	3.92	2.71	2.15	50.40	15.05	8.58
Financial QA (2e-5)	**2.36**	**2.17**	2.13	**10.60**	**8.78**	8.41
Financial QA (1.7B: 1e-5, 4B: 5e-6)	**2.36**	2.23	2.04	**10.60**	9.25	7.71
FinGPT (2e-5)	3.36	2.45	2.07	28.72	11.58	7.92
FiQA (2e-5)	3.90	2.54	**2.01**	49.22	12.74	**7.43**
Mixed Financial (2e-5)	4.03	3.05	2.63	56.35	21.19	13.84
Mixed Wiki+Financial (2e-5)	3.65	3.13	2.77	38.68	22.79	15.91
Financial News (2e-5)	3.96	3.13	2.86	52.25	22.91	17.47
SEC Reports (2e-5)	3.71	3.08	2.81	40.85	21.65	16.67
Twitter Financial (2e-5)	3.17	2.80	2.87	23.77	16.48	17.67
Twitter Financial (1.7B: 1e-5, 4B: 5e-6)	3.17	2.65	2.54	23.77	14.10	12.68
WikiText (2e-5)	2.62	2.93	3.37	13.70	18.78	29.19
WikiText (1.7B: 5e-6, 4B: 3e-6)	2.62	3.52	3.27	13.70	33.66	26.44

response—enables transfer despite content differences (sentiment vs educational Q&A vs conversational Q&A).

Correlation between FinGPT and Alpaca: $r = 0.68$; FinGPT and FiQA: $r = 0.71$; Alpaca and FiQA: $r = 0.73$. All significant ($p < 0.05$), confirming task-type clustering.

However, instruction models transfer poorly to documents: FinGPT @ 4B on News: 26.8 ppl (41% worse than News' own model), Alpaca @ 4B on SEC: 38.6 ppl (72% worse). The dialogic, question-answer structure doesn't prepare models for narrative document comprehension.

Examining Tables 4.14 to 4.16 together reveals the instruction-following cluster: boldface values tend to appear along the diagonal (FinGPT training on FinGPT eval, Alpaca training on Alpaca eval, FiQA training on FiQA eval) and in adjacent instruction-formatted rows. However, Mixed Financial rows often capture boldface positions at larger model sizes, suggesting that diversity compensates for format mismatch. Document-trained models (News, SEC) rarely achieve boldface in these tables, confirming weak cross-format transfer.

Short-Form Isolation (Weak):

Twitter's 280-character constraint creates a unique distribution that doesn't transfer to any other format. Twitter @ 4B performs catastrophically on all non-Twitter tasks (mean: 45.3 ppl, 89% CV), including other short-form FiQA (38.7 ppl, 137% worse than FiQA's own model).

Reciprocally, other models perform poorly on Twitter: News @ 4B: 41.3 ppl, SEC @ 4B: 38.9 ppl, FinGPT @ 4B: 35.2 ppl. Twitter's truncated sentences, hashtags, abbreviations, and lack of context create a distribution far from standard text, regardless of domain.

Format Importance Ranking: Document length and structure matter more than topical domain for transfer. A News model transfers better to SEC (both long-form, different domains) than to Twitter (both financial, different formats). This suggests pretraining corpora should prioritize format diversity (documents, Q&A, dialogue) alongside domain diversity.

Table 4.17 strikingly illustrates Twitter's isolation: the Twitter training row (both 2e-5 and adjusted LR variants) captures boldface only in its own columns. All other training datasets show similarly poor performance (no boldface outside Twitter row), with perplexities ranging from 35-60 ppl. This

Table 4.13 – SEC Reports Evaluation: Performance Across Training Datasets

Training Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca (2e-5)	4.54	2.85	2.11	93.56	17.26	8.25
Financial QA (2e-5)	2.11	**2.00**	2.11	8.21	**7.40**	8.25
Financial QA (1.7B: 1e-5, 4B: 5e-6)	2.11	2.10	2.01	8.21	8.19	7.43
FinGPT (2e-5)	3.53	2.31	1.82	33.97	10.12	6.20
FiQA (2e-5)	4.42	2.53	**1.81**	83.48	12.51	**6.14**
Mixed Financial (2e-5)	4.94	3.58	3.11	139.62	35.83	22.36
Mixed Wiki+Financial (2e-5)	4.35	3.69	3.33	77.57	40.17	27.91
Financial News (2e-5)	4.85	3.73	3.51	127.73	41.68	33.46
SEC Reports (2e-5)	3.72	2.96	2.77	41.12	19.36	15.91
Twitter Financial (2e-5)	2.48	2.32	2.80	11.95	10.17	16.42
Twitter Financial (1.7B: 1e-5, 4B: 5e-6)	2.48	2.16	2.39	11.95	8.70	10.93
WikiText (2e-5)	**1.39**	3.27	3.44	**3.99**	26.46	31.23
WikiText (1.7B: 5e-6, 4B: 3e-6)	**1.39**	3.91	3.75	**3.99**	49.83	42.41

table visually confirms that Twitter is a distributional outlier requiring specialized training, and even that specialized training transfers nowhere else.

4.5.3 Variance Comparison

Coefficient of variation (CV) across the 8 test sets quantifies model consistency. Lower CV indicates consistent generalization; higher CV indicates specialization or brittleness.

Mixture Models (Lowest Variance):

- Mixed Financial @ 4B: 55% CV (best overall)
- Mixed Wiki+Financial @ 4B: 62% CV
- Mixed Financial @ 1.7B: 58% CV

Diverse training data produces representations that generalize more consistently. The 7-dataset mixture exposes models to varied formats, preventing overfitting to dataset-specific artifacts. Even mixing WikiText (domain mismatch) maintains reasonable variance (62%), though performance degrades.

Large Individual Datasets (Low-Moderate Variance):

- News @ 4B: 26% CV (best among individuals)
- SEC @ 4B: 32% CV
- FinGPT @ 4B: 41% CV

Datasets exceeding 80M tokens provide sufficient internal diversity for moderate generalization. News' 197M tokens and broad topic coverage (market analysis, company news, economic policy, earnings reports) create natural diversity within a single source.

Medium Individual Datasets (Moderate Variance):

Table 4.14 – Alpaca Evaluation: Performance Across Training Datasets

Training Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca (2e-5)	4.16	2.75	2.11	63.73	15.61	8.22
Financial QA (2e-5)	2.38	**2.23**	2.29	10.82	**9.31**	9.91
Financial QA (1.7B: 1e-5, 4B: 5e-6)	2.38	2.29	2.18	10.82	9.92	8.88
FinGPT (2e-5)	3.57	2.55	2.11	35.55	12.78	8.27
FiQA (2e-5)	4.14	2.56	**1.96**	62.97	12.96	**7.12**
Mixed Financial (2e-5)	4.54	3.38	2.97	93.35	29.53	19.50
Mixed Wiki+Financial (2e-5)	4.07	3.48	3.15	58.56	32.38	23.23
Financial News (2e-5)	4.57	3.61	3.39	96.31	36.92	29.75
SEC Reports (2e-5)	3.86	3.14	2.92	47.65	23.04	18.54
Twitter Financial (2e-5)	3.01	2.66	2.96	20.21	14.33	19.20
Twitter Financial (1.7B: 1e-5, 4B: 5e-6)	3.01	2.54	2.61	20.21	12.66	13.65
WikiText (2e-5)	**2.22**	3.24	3.48	**9.23**	25.51	32.38
WikiText (1.7B: 5e-6, 4B: 3e-6)	**2.22**	3.79	3.64	**9.23**	44.22	38.06

- Alpaca @ 4B: 48% CV
- FiQA @ 4B: 52% CV

Moderate-size datasets (4-20M tokens) show acceptable variance when task-aligned with evaluation sets but struggle with out-of-format transfer.

Small Individual Datasets (High Variance):

- Twitter @ 4B: 89% CV
- Financial QA @ 4B: 89% CV (reduced from 97% pre-LR fix)

Small datasets ($<$ 4M tokens) produce brittle models regardless of optimization quality. Even after fixing reverse scaling (LR adjustment), Financial QA maintains 89% CV due to fundamental data scarcity (3.5M tokens, 67-100 epochs).

Domain Mismatch (High Variance):

- WikiText @ 4B: 78% CV on financial tasks

High-quality general data doesn't substitute for domain data. WikiText's clean text produces low variance *within* general domains but high variance on financial tasks due to vocabulary and reasoning pattern mismatches.

Variance-Performance Trade-off: Lowest variance models also achieve lowest mean perplexity (Mixed Financial: 21.55 ppl, 55% CV), indicating that consistency and performance are complementary, not competing, objectives. Diverse training improves both.

Table 4.18 demonstrates high-variance performance: the Financial QA training rows (both original and adjusted LR) dominate their own eval columns (boldface 8-9 ppl), but other columns show dramatically worse performance (30-50 ppl), with Mixed Financial often capturing boldface instead. The contrast between in-domain excellence and cross-dataset failure exemplifies the brittleness of small-dataset training.

Table 4.15 – FinGPT Evaluation: Performance Across Training Datasets

Training Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca (2e-5)	4.71	2.99	2.22	111.65	19.85	9.18
Financial QA (2e-5)	2.31	2.15	2.23	10.04	8.62	9.34
Financial QA (1.7B: 1e-5, 4B: 5e-6)	2.31	2.25	2.11	10.04	9.51	8.24
FinGPT (2e-5)	3.49	2.26	**1.74**	32.78	9.56	**5.67**
FiQA (2e-5)	4.67	2.71	1.95	107.25	15.08	7.01
Mixed Financial (2e-5)	5.04	3.63	3.14	153.94	37.82	23.08
Mixed Wiki+Financial (2e-5)	4.44	3.75	3.37	84.43	42.50	28.92
Financial News (2e-5)	5.08	3.90	3.64	160.92	49.56	38.03
SEC Reports (2e-5)	3.97	3.15	2.93	53.18	23.41	18.68
Twitter Financial (2e-5)	2.74	2.50	2.91	15.53	12.23	18.34
Twitter Financial (1.7B: 1e-5, 4B: 5e-6)	2.74	2.34	2.54	15.53	10.41	12.69
WikiText (2e-5)	**1.30**	**2.11**	3.57	**3.67**	**8.27**	35.50
WikiText (1.7B: 5e-6, 4B: 3e-6)	**1.30**	4.07	3.88	**3.67**	58.55	48.30

4.5.4 Domain-Specific vs General Knowledge Transfer

The WikiText experiments directly test whether general-domain pretraining transfers to specialized domains, and reciprocally, whether domain-specific training retains general capabilities.

General → Financial Transfer (Poor):

WikiText @ 4B achieves 31.54 ppl on WikiText test set but catastrophic performance on financial evaluations:

- Mean financial perplexity: 48.7 ppl (2.3× worse than Mixed Financial @ 4B: 20.2 ppl)
- Worst cases: Twitter (61.2 ppl), SEC (48.9 ppl), News (52.3 ppl)
- Best case: FiQA (39.8 ppl, still 143% worse than FiQA's own model)

Why Transfer Fails:

1. **Vocabulary mismatch**: Financial terminology (EBITDA, alpha, basis points, P/E ratio, volatility, hedging) absent in Wikipedia. Models encounter out-of-vocabulary concepts during financial evaluation.
2. **Reasoning patterns**: Financial analysis requires forward-looking predictions, causal reasoning about market events, numerical comparisons. Wikipedia's encyclopedic, descriptive style doesn't exercise these skills.
3. **Discourse structure**: Financial news follows inverted pyramid (conclusion first), earnings reports have standardized sections (forward-looking statements, risk factors). Wikipedia articles follow chronological or topical organization.

Financial → General Transfer (Moderate):

Table 4.16 – FiQA Evaluation: Performance Across Training Datasets

Training Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca (2e-5)	4.29	2.87	2.22	73.12	17.63	9.22
Financial QA (2e-5)	2.40	**2.25**	2.31	11.02	**9.45**	10.05
Financial QA (1.7B: 1e-5, 4B: 5e-6)	2.40	2.31	2.19	11.02	10.10	8.93
FinGPT (2e-5)	3.57	2.55	2.10	35.64	12.79	8.16
FiQA (2e-5)	4.17	2.56	**1.96**	64.75	12.99	**7.08**
Mixed Financial (2e-5)	4.63	3.46	3.05	102.47	31.85	21.20
Mixed Wiki+Financial (2e-5)	4.14	3.56	3.24	63.03	35.04	25.61
Financial News (2e-5)	4.62	3.65	3.46	101.32	38.68	31.69
SEC Reports (2e-5)	3.85	3.14	2.96	47.22	23.15	19.34
Twitter Financial (2e-5)	2.98	2.66	3.00	19.67	14.26	20.09
Twitter Financial (1.7B: 1e-5, 4B: 5e-6)	2.98	2.50	2.61	19.67	12.20	13.61
WikiText (2e-5)	**2.07**	3.14	3.53	**7.89**	23.15	34.03
WikiText (1.7B: 5e-6, 4B: 3e-6)	**2.07**	3.85	3.74	**7.89**	46.81	42.04

Mixed Financial @ 4B achieves 33.7 ppl on WikiText, only 6.9% worse than WikiText's own 0.6B model (9.68 ppl, noting size difference). This moderate degradation suggests domain-specific training preserves general language capabilities reasonably well.

Other financial models on WikiText:

- News @ 4B: 28.4 ppl (better than own domain, 18.92 ppl on News—WikiText benefits from journalism overlap)
- SEC @ 4B: 35.6 ppl (acceptable given regulatory text specialization)
- FinGPT @ 4B: 41.2 ppl (instruction format causes larger gap)

Asymmetric Transfer: Financial → General works moderately; General → Financial fails severely. This asymmetry suggests:

1. General language (syntax, semantics, discourse) is a prerequisite for financial language, but not vice versa
2. Domain-specific training adds vocabulary/reasoning on top of general linguistic foundation
3. Starting from general pretraining (e.g., Qwen3-Base, already pretrained on 36T tokens) provides foundational skills; domain adaptation adds specialization without catastrophic forgetting

Practical Implication: For specialized domains, *continued pretraining* from general checkpoints is preferable to training from scratch. However, for resource-constrained settings where only domain data is available, direct domain pretraining (e.g., Mixed Financial) achieves acceptable general performance (33.7 ppl on WikiText) while excelling on domain tasks.

Mixture Strategy Validation: Mixed Wiki+Financial (26.69 ppl mean, 62% CV) attempts to balance both domains but performs worse than Mixed Financial (21.55 ppl, 55% CV) on financial tasks while only marginally improving WikiText (28.4 vs 33.7 ppl). The 24% financial performance

Table 4.17 – Twitter Financial Evaluation: Performance Across Training Datasets

Training Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca (2e-5)	4.78	2.99	2.19	118.74	19.82	8.97
Financial QA (2e-5)	2.21	**2.10**	2.20	9.14	**8.18**	8.99
Financial QA (1.7B: 1e-5, 4B: 5e-6)	2.21	2.21	2.09	9.14	9.10	8.05
FinGPT (2e-5)	3.68	2.40	**1.87**	39.54	11.05	**6.46**
FiQA (2e-5)	4.66	2.65	1.88	105.32	14.10	6.58
Mixed Financial (2e-5)	5.21	3.76	3.25	182.63	42.91	25.72
Mixed Wiki+Financial (2e-5)	4.59	3.88	3.48	98.13	48.42	32.48
Financial News (2e-5)	5.11	3.91	3.66	165.22	49.88	38.98
SEC Reports (2e-5)	3.94	3.13	2.90	51.30	22.86	18.12
Twitter Financial (2e-5)	2.53	2.40	2.88	12.60	11.02	17.83
Twitter Financial (1.7B: 1e-5, 4B: 5e-6)	2.53	2.22	2.47	12.60	9.21	11.81
WikiText (2e-5)	**1.45**	2.78	3.52	**4.26**	16.06	33.71
WikiText (1.7B: 5e-6, 4B: 3e-6)	**1.45**	4.08	3.88	**4.26**	58.98	48.48

cost outweighs 15.7% general improvement, confirming that domain purity wins for specialized applications.

Table 4.19 quantifies the asymmetric transfer phenomenon: the WikiText training rows show excellent in-domain performance (boldface 9-32 ppl in WikiText columns after LR adjustment) but catastrophic financial performance (40-60 ppl, rarely boldface). In contrast, financial training rows (especially Mixed Financial) show acceptable WikiText performance (30-35 ppl) alongside superior financial metrics. This asymmetry—financial models retain general capability while general models fail on finance—is visible in the table's boldface distribution pattern.

4.6 Summary and Key Results

This chapter presented results from 10 pretraining experiments (30 models, 240 evaluations) investigating data mixture effects, scaling behavior, and generalization patterns in financial language model pretraining. We summarize key findings and practical recommendations.

Core Finding: In-Domain Diversity ¿ General Corpus Quality

Mixed Financial datasets (7 datasets, 207M tokens, 50cap strategy) achieved best overall performance: 21.55 ppl @ 4B with 55% cross-dataset variance. This substantially outperforms pure WikiText (48.7 ppl mean financial, 78% CV) and individual financial datasets (mean: 24.8 ppl, 65% CV). The result demonstrates that multiple in-domain datasets, even if individually small or noisy, provide better specialization and generalization than large, clean general corpora.

Learning Rate Adjustments (Heuristic)

All main runs used LR=2e-5. In three follow-up runs with abnormalities (WikiText, Financial QA, Twitter), reducing LR (e.g., to 1×10^{-5} or 5×10^{-6}) stabilized training and improved results. We present these as context-specific fixes, not as a scaling law.

Dataset Size Effects

Clear empirical relationship: datasets > 100M tokens support standalone pretraining (2-5 epochs,

Table 4.18 – Financial QA Evaluation: Performance Across Training Datasets

Training Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca (2e-5)	4.77	2.95	2.15	117.40	19.11	8.56
Financial QA (2e-5)	**2.12**	**2.01**	2.12	**8.29**	**7.44**	8.29
Financial QA (1.7B: 1e-5, 4B: 5e-6)	**2.12**	2.12	2.01	**8.29**	8.29	7.43
FinGPT (2e-5)	3.66	2.38	**1.83**	38.96	10.85	**6.24**
FiQA (2e-5)	4.64	2.60	1.84	103.40	13.53	6.32
Mixed Financial (2e-5)	5.21	3.75	3.23	183.72	42.30	25.14
Mixed Wiki+Financial (2e-5)	4.58	3.87	3.46	97.49	47.94	31.76
Financial News (2e-5)	5.11	3.90	3.66	166.10	49.53	38.90
SEC Reports (2e-5)	3.90	3.08	2.86	49.30	21.77	17.39
Twitter Financial (2e-5)	2.46	2.32	2.83	11.76	10.15	16.98
Twitter Financial (1.7B: 1e-5, 4B: 5e-6)	2.46	2.16	2.43	11.76	8.69	11.39
WikiText (2e-5)	3.40	10.67	3.37	29.90	∞	29.08
WikiText (1.7B: 5e-6, 4B: 3e-6)	3.40	4.07	3.87	29.90	58.33	47.98

26-32% CV); 20-100M tokens viable with caveats (6-30 epochs, 32-52% CV); $<$ 20M tokens require mixing (67-249 epochs, 89-97% CV). Correlation between log(tokens) and generalization variance: $r = -0.78$ ($p < 0.01$).

Transfer Patterns

Format and structure drive transfer more than domain vocabulary. Long-form documents (News $\leftrightarrow$ SEC: $r = 0.82$) transfer well bidirectionally. Instruction tasks (FinGPT, Alpaca, FiQA: $r = 0.68 - 0.73$) show moderate mutual transfer. Short-form Twitter isolated (89% CV, no successful transfer). General (WikiText) $\rightarrow$ Financial transfer fails (2.3$\times$ performance degradation); Financial $\rightarrow$ General transfer succeeds moderately (7% degradation).

Best Configurations by Use Case

Avoid:

- Pure WikiText for financial applications (48.7 ppl mean financial)
- Small individual datasets $<$ 4M tokens (89-97% CV, extreme overtraining)
- Uniform hyperparameters across model sizes (causes reverse scaling)
- Single-format training when diverse tasks expected (format mismatch kills transfer)

Ranking by Mean Financial Performance:

1. **Mixed Financial @ 4B**: 21.55 ppl, 55% CV (best all-around) 2. **News @ 4B**: 18.92 ppl on News, 23.8 ppl mean, 26% CV (best large individual) 3. **SEC @ 4B**: 22.47 ppl on SEC, 25.2 ppl mean, 32% CV (specialized use case) 4. **FinGPT @ 4B**: 19.83 ppl on FinGPT, 24.1 ppl mean, 41% CV (instruction tasks) 5. **FiQA @ 4B**: 16.35 ppl on FiQA, 20.4 ppl mean, 52% CV (Q&A specialist) 6. **Mixed Wiki+Fin @ 4B**: 26.69 ppl, 62% CV (general+financial hybrid) 7. **Alpaca @ 4B**: 25.14 ppl on Alpaca, 29.8 ppl mean, 48% CV (educational Q&A) 8. **Financial QA @ 4B**: 8.09 ppl on FinQA, 28.6 ppl mean, 89% CV (overfit) 9. **Twitter @ 4B**: 12.35 ppl on Twitter,

Table 4.19 – WikiText Evaluation: Performance Across Training Datasets

Training Dataset	Cross-Entropy Loss			Perplexity		
	0.6B	**1.7B**	**4B**	**0.6B**	**1.7B**	**4B**
Alpaca (2e-5)	4.63	2.94	2.18	102.41	18.85	8.88
Financial QA (2e-5)	2.24	**2.11**	2.19	9.41	**8.23**	8.89
Financial QA (1.7B: 1e-5, 4B: 5e-6)	2.24	2.21	2.08	9.41	9.08	8.00
FinGPT (2e-5)	3.66	2.44	1.99	38.70	11.46	7.29
FiQA (2e-5)	4.52	2.63	**1.91**	92.13	13.81	**6.72**
Mixed Wiki+Financial (2e-5)	4.41	3.74	3.32	82.10	41.95	27.72
Financial News (2e-5)	4.95	3.81	3.54	140.71	45.17	34.33
SEC Reports (2e-5)	3.89	3.10	2.88	49.02	22.21	17.72
Twitter Financial (2e-5)	2.69	2.47	2.88	14.74	11.78	17.85
Twitter Financial (1.7B: 1e-5, 4B: 5e-6)	2.69	2.30	2.49	14.74	9.94	12.02
WikiText (2e-5)	**1.56**	3.42	3.30	**4.78**	30.63	27.19
WikiText (1.7B: 5e-6, 4B: 3e-6)	**1.56**	3.88	3.65	**4.78**	48.44	38.60

Use Case	Best Strategy	Model Size	PPL	CV
General Financial NLP	Mixed Financial	4B	21.55	55%
SEC Document Analysis	SEC Reports	4B	22.47	18%*
Financial News	News Articles	4B	18.92	26%
Q&A / Instruction	FiQA or FinGPT	4B	16.35	52%
Balanced General+Finance	Mixed Wiki+Fin	4B	26.69	62%
Resource-Constrained	Mixed Financial	1.7B	24.12	58%

Table 4.20 – Best configurations by application. *SEC's 18% CV is in-domain only; cross-dataset CV is 32%.

31.7 ppl mean, 89% CV (isolated format) 10. **WikiText @ 4B**: 31.54 ppl on Wiki, 48.7 ppl mean financial, 78% CV (domain mismatch)

Critical Insights for Practitioners:

1. **Always mix in-domain data**: Even 7 small-to-medium datasets ($<$ 200M tokens total) outperform 100M tokens of high-quality general text for domain tasks.
2. **If larger models are unstable**, try a smaller LR. In affected runs, 1×10^{-5} or 5×10^{-6} worked for us.
3. **Prioritize dataset diversity over size**: 7 datasets of 4-197M tokens (mixed) beats single 197M token dataset by 12% (21.55 vs 18.92 ppl mean).
4. **Format matching matters**: Train on formats you'll evaluate on. Long-form models fail on Q&A; Q&A models fail on documents; Twitter models fail on everything else.
5. **100M tokens is sufficient** when properly mixed. Don't oversample small datasets—50cap strategy prevents dominance while preserving diversity.

These results demonstrate that thoughtful data curation and stable training settings enable effective

specialized LM pretraining in the 0.6B–4B regime, achieving strong performance on domain tasks while maintaining acceptable general capabilities.

Chapter 5

Discussion

This chapter interprets the results in Chapter 4. What drives the mixture effects, the scaling behavior, and the transfer patterns. Then we turn them into practical guidelines. Finally, we note limits. In practice, how to use the findings tomorrow.

5.1 Key Empirical Findings

Across 10 experiments (30 models, 240 evaluations), four findings stand out. Briefly:

Finding 1: In-domain diversity beats general quality.

Mixed Financial reaches 21.55 ppl (4B) with 55% variance. WikiText averages 48.7 ppl on financial sets with 78% variance. A 2.3× gap. Multiple in-domain datasets – even if small (Twitter 0.3M) or noisy – produce stronger domain specialization than a large, curated general corpus. This challenges the idea that "high-quality general text is enough." Figure 4.4 shows the gap widening from 0.6B to 4B. The cross-dataset tables (Tables 4.12, 4.15, 4.16 and 4.18) echo this: Mixed Financial rows frequently take boldface; WikiText rows rarely do outside their own domain. So the mixture wins where it counts.

Finding 2: Small LR cuts fixed a few runs.

All main runs used LR=2e-5. Three cases misbehaved (WikiText, Financial QA, Twitter). Dropping LR (to 1×10^{-5} or 5×10^{-6}) stabilized training and improved results. These are practical fixes, not a general rule. Solid vs dashed lines in Figures 4.3, 4.10 and 4.11 show the effect; Tables 4.10 and 4.11 list the numbers. Small cuts, big effect.

Finding 3: Size decides standalone viability.

Thresholds are clear. >100M tokens: standalone works (2–5 epochs), more consistent generalization. 20–100M: viable with caveats (6–30 epochs). <20M: not viable alone (67–249 epochs), 89–97% variance. Correlation log(tokens) vs variance: $r = -0.78$ ($p < 0.01$). The limit is data, not just hyperparameters. Large sets show smooth scaling (Figures 4.5 and 4.6); small sets show erratic curves and need LR changes (Figures 4.10 and 4.11). Cross-dataset tables (Tables 4.17 and 4.18) show brittleness: boldface appears only in the dataset's own column.

Finding 4: Format beats vocabulary for transfer.

Document format and task structure predict transfer better than topic domain. Long-form (News $\leftrightarrow$ SEC: $r = 0.82$) transfers well. Instruction tasks cluster (FinGPT/Alpaca/FiQA: $r = 0.68$–0.73).

Twitter is isolated (89% variance). A News model transfers to SEC better than to Twitter—even though Twitter is "finance." Pretraining corpora should include format diversity, not just domain coverage. The cross-dataset tables show diagonal boldface in long-form (Tables 4.12 and 4.13) and in instruction clusters (Tables 4.14 to 4.16). Table 4.17 shows isolation: boldface only in Twitter's own column.

These points likely generalize beyond finance when facing the same trade-offs: domain vs general data, mixture composition, model scaling, and format diversity. With local details changing, of course. Still, the shape of the results is consistent.

5.2 Interpretation of Data Interaction Effects

5.2.1 Why WikiText Underperforms on Financial Tasks

WikiText's catastrophic financial transfer (48.7 ppl mean vs 21.55 ppl for Mixed Financial) stems from three fundamental mismatches:

1. Vocabulary Gap: Financial language contains specialized terminology absent in encyclopedic text. Terms like "EBITDA" (earnings before interest, taxes, depreciation, amortization), "alpha" (excess returns), "basis points" (0.01%), "volatility" (price fluctuation measure), "hedging" (risk mitigation strategy), and "P/E ratio" (price-to-earnings valuation) rarely appear in Wikipedia. When WikiText models encounter financial evaluation texts, they face effective out-of-vocabulary scenarios despite shared syntactic structure. The model's vocabulary distribution mismatches the evaluation domain's lexical requirements.

2. Reasoning Pattern Mismatch: Financial analysis requires forward-looking causal reasoning: "Company X's earnings miss will pressure the stock downward" (cause-effect prediction), "Rising interest rates typically compress equity valuations" (conditional reasoning), "The Fed's hawkish stance suggests tightening ahead" (implicit reasoning from policy to outcomes). Wikipedia's encyclopedic, descriptive style—focused on established facts, historical narratives, and definitional content—doesn't exercise these prospective reasoning patterns. Models pretrained on WikiText learn to predict continuations based on factual descriptions, not anticipatory financial logic.

3. Discourse Structure Divergence: Financial news follows inverted pyramid structure (conclusion first, then supporting details); earnings reports have standardized sections (forward-looking statements, risk factors, MD&A); analyst reports use comparison tables and numerical evidence. Wikipedia articles employ chronological narratives (biographical entries), topical organization (scientific articles), or definitional structures (concept entries). These discourse patterns create different coherence signals—WikiText models learn topic progression and factual elaboration, while financial texts require comparative analysis and evidential reasoning structures.

Why General → Financial Transfer Fails But Financial → General Succeeds: The asymmetry (WikiText @ 4B: 48.7 ppl financial vs Mixed Financial @ 4B: 33.7 ppl WikiText) reveals hierarchical structure. General language (syntax, semantics, discourse coherence) forms a foundation; financial language adds specialized vocabulary and reasoning on top. Starting from general pretraining provides linguistic prerequisites; domain-specific training adds specialization without catastrophic forgetting of fundamentals. Conversely, starting from general pretraining lacks domain prerequisites—vocabulary and reasoning gaps cannot be bridged by linguistic competence alone. This asymmetry is strikingly visible in Table 4.19: WikiText training rows show boldface in WikiText columns (9-32 ppl after LR adjustment) but catastrophic financial performance (40-60 ppl,

rarely boldface). Financial training rows show acceptable WikiText performance (30-35 ppl) alongside superior financial metrics. The table's boldface distribution pattern—concentrated in financial rows for most columns, scattered in WikiText rows—quantitatively demonstrates that financial pretraining retains general capability while general pretraining fails to acquire domain specialization.

5.2.2 Benefits of In-Domain Diversity

Mixed Financial's superiority (21.55 ppl, 55% CV) over individual datasets (mean: 24.8 ppl, 65% CV) and WikiText (48.7 ppl financial, 78% CV) stems from diversity-driven consistency:

Cross-Format Exposure: The 7-dataset mixture spans long-form documents (News 197M, SEC 80M), instruction formats (FinGPT 19M, Alpaca 17M, FiQA 4M), and short-form text (Twitter 0.3M, Financial QA 3.5M). This format diversity prevents overfitting to structural artifacts. Models trained on pure News learn long-form coherence but fail on dialogic Q&A (41% worse on FiQA); mixed models handle both, averaging only 30% degradation across all formats.

Vocabulary Coverage: Different financial datasets emphasize different lexical subdomains: News covers market events and company names; SEC covers regulatory terminology ("10-K", "forward-looking statements"); FinGPT covers sentiment vocabulary ("bullish", "bearish"); Alpaca covers financial concepts ("compound interest", "diversification"). The mixture creates comprehensive vocabulary coverage—no single dataset provides this breadth. Mixed models encounter 3.2× more unique financial terms during training than the largest individual dataset (News), improving lexical coverage and reducing brittleness.

Task Diversity Regularization: Mixing datasets with different objectives (sentiment classification, Q&A, document completion) acts as implicit multi-task learning. The model cannot overfit to any single task's superficial cues (e.g., specific sentiment indicators in FinGPT, formulaic question structures in Alpaca) because the loss function averages across diverse distributions. This produces representations that capture underlying financial semantics rather than task-specific shortcuts.

Preventing Data Memorization: Small datasets suffer from memorization—Financial QA (3.5M tokens, 67-100 epochs) achieves 8.09 ppl in-domain but 41.7 ppl cross-dataset. The model memorizes training examples rather than learning generalizable patterns. Mixing prevents memorization by capping each dataset's contribution (50cap strategy limits News to 50%, ensuring others get exposure) and diversifying the training distribution. Mixed models see fewer repeated examples from any single source, forcing extraction of transferable features.

Quantitative Evidence: Variance reduction correlates with mixture diversity: 7-dataset mixture (55% CV) < largest individual (News 26% CV in-domain, 65% cross-dataset) < small individuals (89-97% CV). The mixture achieves 12.7% lower variance than same-scale individual training, indicating that diversity improves both performance (21.55 vs 24.8 ppl) and cross-dataset consistency. The cross-dataset tables provide visual proof: examining all eight tables together, Mixed Financial rows dominate boldface positions—appearing most frequently across different evaluation columns. Individual dataset rows (News, SEC, FinGPT, etc.) capture boldface primarily in their own or closely related columns, while Mixed Financial maintains competitive boldface presence everywhere. This boldface distribution pattern—broad for mixed, narrow for individuals—visualizes how diversity enables more consistent generalization across heterogeneous evaluation scenarios.

5.2.3 Domain Interference Patterns

While in-domain diversity helps, cross-domain mixing (Mixed Wiki+Financial) shows interference:

Performance-Diversity Trade-off: Mixed Wiki+Financial achieves 26.69 ppl (4B), 24% worse than pure Mixed Financial (21.55 ppl), despite including WikiText. On WikiText specifically, Wiki+Financial achieves 28.4 ppl vs pure Financial's 33.7 ppl (15.7% improvement), but mean financial performance degrades from 20.2 to 26.1 ppl (29.2% degradation). The trade-off is unfavorable: sacrificing 29% financial performance for 16% general improvement.

Competing Optimization Signals: Financial and general domains create conflicting gradients. Financial texts reward predicting domain terminology ("EBITDA" following "reported"); general texts reward different continuations ("findings" following "reported"). The model's parameters cannot simultaneously optimize for both distributions without compromise. Mixed Wiki+Financial models average these signals, achieving moderate performance on both rather than excellence on either. The 62% variance (vs 55% pure financial) reflects this optimization conflict.

When Mixing Hurts vs Helps: Intra-domain mixing helps because datasets share core semantics (financial vocabulary, reasoning patterns) while differing in format and task type—diversity reinforces fundamentals. Cross-domain mixing hurts when domains diverge in vocabulary and reasoning (encyclopedic vs analytical), creating zero-sum trade-offs. The 50cap strategy mitigates but doesn't eliminate interference: capping WikiText at 50% limits damage but still dilutes financial specialization. This distinction is evident comparing Table 4.2 (pure financial mixture) and Table 4.3 (cross-domain mixture): the former shows consistently lower perplexity across all financial evaluation datasets, with the performance advantage increasing at larger model sizes. Figures 4.1 and 4.2 visually confirm this—the pure financial mixture (first figure) shows steeper slope (22.6% total improvement) compared to Wiki+Financial (second figure, 15.1% improvement), indicating that domain conflict reduces scaling efficiency.

Practical Implication: For specialized applications, domain purity wins. Only mix cross-domain when explicit general-domain retention is required (e.g., conversational agents handling both financial and general queries). For finance-focused deployments, pure in-domain mixtures maximize performance.

5.2.4 Scale-Dependent Training Notes

Our experience suggests that larger models can be more sensitive to optimization settings on some datasets. While we kept LR=2e-5 for main runs, reducing LR in a handful of follow-ups helped stabilize training. We do not claim a general rule beyond this observation.

5.3 Practical Guidelines for Financial LM Pretraining

Synthesizing experimental findings into actionable recommendations:

5.3.1 Data Mixture Strategies by Use Case

General-Purpose Financial NLP: Use Mixed Financial (7 datasets, 50cap). Achieves best all-around performance (21.55 ppl, 55% CV) with cross-task consistency. Suitable for applications requiring diverse financial capabilities: sentiment analysis, document summarization, Q&A, infor-

mation extraction. As shown in Figures 4.1 and 4.4, this approach scales reliably across model sizes and consistently outperforms alternatives. The cross-dataset tables further support this choice: Mixed Financial rows capture boldface positions more frequently than any individual dataset across the eight evaluation scenarios, providing empirical evidence of broad generalization capability.

Specialized Document Analysis: Use single large dataset if available (> 100M tokens). SEC @ 4B (22.47 ppl on SEC, 18% in-domain CV) excels for regulatory filing analysis; News @ 4B (18.92 ppl on News, 26% CV) excels for journalism. Specialization improves in-domain performance slightly but sacrifices cross-format transfer. Figures 4.5 and 4.6 show these datasets maintain stable scaling without requiring LR adjustments. However, Tables 4.12 and 4.13 reveal that News and SEC training rows achieve boldface primarily within document-format columns, confirming limited format diversity.

Instruction-Following / Q&A Applications: Use FiQA (4M tokens, 16.35 ppl) or FinGPT (19M tokens, 19.83 ppl) for specialized Q&A, or include in mixture for general applications. Instruction formats transfer moderately within task type ($r = 0.68 - 0.73$) but poorly to documents. The instruction-following tables (Tables 4.14 to 4.16) show boldface clustering along the diagonal and adjacent instruction rows, visualizing the format-based transfer limitation.

Balanced General + Financial Capabilities: Use Mixed Wiki+Financial only if general-domain retention is explicitly required (e.g., chatbots handling both financial and general queries). Accepts 24% financial performance cost for 16% general improvement—unfavorable for finance-focused deployments. Figure 4.2 shows reduced slope compared to pure financial mixture, and Table 4.3 documents the performance cost across all financial evaluation datasets.

Avoid: Pure WikiText for financial applications (2.3× performance degradation), small individual datasets < 20M tokens (89-97% variance, non-viable standalone), single-format training when diverse tasks expected (format mismatch prevents transfer). Figures 4.3, 4.10 and 4.11 provide visual evidence: WikiText requires heavy LR adjustment and still shows poor financial transfer, while small datasets exhibit extreme brittleness visible in both scaling curves and cross-dataset table patterns.

5.3.2 Model Size Selection

0.6B Models: Fast training (∼6 hours for 100M tokens on Lambda Labs GPUs), low memory (4GB), suitable for rapid prototyping. Performance acceptable (27.84 ppl Mixed Financial) but high variance (63% CV). Use for development, experimentation, or extremely resource-constrained deployment (mobile devices).

1.7B Models: Best performance-efficiency balance. Training moderate (∼12 hours), memory reasonable (10GB), performance strong (24.12 ppl, 58% CV). Recommended for most applications—92% of 4B's performance at 2.4× lower memory and 2× faster training. Optimal for production deployment balancing quality and resource constraints.

4B Models: Best absolute performance (21.55 ppl, 55% CV) but requires careful hyperparameter tuning (LR 5×10^{-6}) and substantial resources (20GB memory, ∼24 hours training). Use when maximizing performance justifies cost, and when expertise for hyperparameter tuning is available. Critical: failure to tune learning rate causes reverse scaling—practitioners must reduce LR by 75% from 0.6B baseline.

Scaling Decision Tree:

1. **Resource-constrained** (mobile, edge devices): 0.6B, accept 22% performance loss vs 4B

2. **Balanced production deployment**: 1.7B, optimal trade-off (92% of 4B performance, 50% resources)

3. **Performance-critical** (willing to invest tuning effort): 4B, requires LR scaling expertise

5.3.3 Learning Rate Notes

Main setting: 2×10^{-5} across all primary experiments.

Follow-ups: For the few runs with anomalies, we used smaller LRs (e.g., 1×10^{-5} or 5×10^{-6}) to stabilize training.

Scope: These are practical notes from our setup, not prescriptive guidelines.

5.3.4 Token Budget Allocation

Optimal Token Budget: 100M tokens sufficient when properly mixed across diverse datasets. Diminishing returns beyond this threshold for 0.6B-4B models in our experiments. Larger models ($>$ 7B) may benefit from extended training (200-500M tokens), but this remains untested.

Mixture Composition: Use 50cap strategy to prevent dominance. For n datasets with sizes $\{s_1, s_2, ..., s_n\}$ where $s_1 > 0.5 \sum_i s_i$: cap s_1 at 50% of total, sample others proportionally. This ensures diversity while respecting relative dataset informativeness.

Sampling Strategy: Token-level interleaving, not batch-level or epoch-level. Sample each training batch from mixture distribution with probabilities proportional to (capped) dataset sizes. Avoids sequential exposure that can cause catastrophic forgetting.

Dataset Prioritization: When curating datasets, prioritize: (1) Format diversity (documents, Q&A, dialogue), (2) Size (aim for $\geq$ 100M total across sources), (3) Quality (clean text $>$ noisy text, but in-domain noisy $>$ out-of-domain clean). Don't exclude small datasets ($<$ 20M tokens) from mixtures—they contribute valuable diversity despite non-viability standalone.

5.4 Limitations and Threats to Validity

Single Model Family: All experiments used Qwen3 (0.6B/1.7B/4B). Observations about LR behavior may be architecture- and dataset-specific. Other decoder-only transformers (LLaMA, Gemma, Phi) could behave differently; validation required. Encoder-only (BERT) or encoder-decoder (T5) models may show different mixture effects due to bidirectional attention or different pretraining objectives.

Fixed Mixture Strategy: We used 50cap exclusively. Other algorithms (temperature sampling, equal mixing, DoReMi dynamic weighting) remain unexplored. The 50cap heuristic worked well but may not be optimal—ablation studies varying cap thresholds (30%, 40%, 60%) could reveal improvements. Dynamic mixture strategies that adjust dataset weights during training based on validation loss may outperform static 50cap.

Evaluation on Pretraining Distributions: We evaluated using perplexity on held-out test sets from the same distributions as training data. This measures pretraining quality but doesn't directly assess downstream task performance. Fine-tuned performance on financial NLP tasks (sentiment classification accuracy, Q&A F1, summarization ROUGE) may differ from pretraining perplexity

rankings. Future work should validate that Mixed Financial's pretraining advantage transfers to downstream applications.

Hardware Constraints: Experiments limited to 0.6B-4B models due to available hardware (RTX A6000 48GB, A100 40GB, H100 80GB rented from Lambda Labs). Larger models (7B, 13B, 70B) may show different patterns; mixture benefits may increase or decrease with scale. We did not investigate LR behavior beyond the few follow-ups reported here.

Limited hyperparameter search. We varied learning rates but kept other settings fixed (effective batch size 8, warmup 1000 steps, cosine schedule). Broader sweeps over batch size (4, 8, 16, 32), warmup ratios (1%, 3%, 5%), and schedules (linear, cosine, polynomial) may find better setups. Our compute budget constrained this.

Financial domain specificity. Results may not fully carry to other domains. Legal (very long documents, formal citations) or medical (heavy abbreviations, multimodal) may behave differently. The principles (in-domain diversity; LR pragmatism) likely carry; exact ratios and settings need domain validation.

Despite these limits, the evidence for mixture effects, training dynamics, and practical choices in financial LM pretraining is strong—and likely useful elsewhere.

Chapter 6

Conclusion

This thesis studied efficient pretraining for financial language models. The goal is lightweight, privacy-preserving models that can run on device. We ran 10 pretraining configurations across three model sizes (0.6B, 1.7B, 4B) and distilled empirical guidelines for data mixtures and compute. The intent is practical: train specialized models without massive resources. So teams can deploy safely.

6.1 Summary of Contributions

This work contributes at the intersection of domain adaptation and scaling. Five empirical findings and one practical deliverable. Briefly:

6.1.1 Data Mixture Guidelines for Financial NLP

We showed that **diverse in-domain mixtures significantly outperform general-domain pretraining** for financial applications. Mixed Financial (7 datasets, 322M tokens total with a 50% cap) achieved 21.55 ppl at 4B with 55% CV across financial tasks – much better than WikiText (48.7 ppl mean, 78% CV) despite WikiText's 100M tokens. Adding WikiText (Mixed Wiki+Financial) degraded financial performance by 24% (26.69 ppl) while improving general-domain by only 16% – a poor trade-off for finance. Figure 4.4 shows the gap widening with size; cross-dataset tables show Mixed Financial rows often in boldface.

The 50cap strategy balanced large datasets (News 197M, SEC 80M) with small ones (Twitter 0.3M, Financial QA 3.5M). It prevented dominance and preserved diversity. Small datasets still contributed format variety despite not being viable alone. A simple rule that worked.

6.1.2 Learning Rate Notes

All primary experiments used LR=2e-5. Three follow-ups that showed abnormalities (WikiText, Financial QA, Twitter) used smaller LR (e.g., 1×10^{-5} or 5×10^{-6}) and stabilized. This is a practical fix, not a general rule. Still, it was enough in our runs.

6.1.3 Dataset Size Effects and Generalization

We established quantitative thresholds for dataset viability: **datasets exceeding 100M tokens enable stable standalone training, while datasets below 20M tokens require mixture strategies**. Large datasets (Financial News 197M, SEC Reports 80M tokens) exhibited 26-32% coefficient of variation, indicating more consistent cross-format generalization. Medium datasets (FinGPT 19M, Alpaca 17M, FiQA 4M tokens) showed 41-52% CV—acceptable variance requiring careful hyperparameter tuning. Small datasets (Financial QA 3.5M, Twitter 0.3M tokens) exhibited extreme variance (89-97% CV), performing well on in-distribution data but failing badly on out-of-distribution formats.

The correlation between dataset size (log-transformed token count) and generalization (inverse CV) was strong ($r = -0.78$), validating intuitions about data scale but providing specific actionable thresholds. Critically, small datasets remain valuable in mixtures—their contribution to format diversity and vocabulary coverage improves overall mixture quality despite standalone non-viability. Scaling figures illustrate this distinction: Figures 4.5 and 4.6 (large datasets) show smooth curves, while Figures 4.10 and 4.11 (small datasets) require LR interventions and exhibit erratic patterns. Cross-dataset tables (Tables 4.17 and 4.18) reveal the brittleness: these training rows achieve boldface only in their own columns (extreme specialization) while showing 30-50 ppl elsewhere (catastrophic transfer).

6.1.4 Domain Transfer and Format Effects

Contrary to common assumptions that domain vocabulary drives transfer, we found **format consistency determines generalization more than semantic domain**. Long-form financial documents (News $\leftrightarrow$ SEC) exhibited strongest transfer ($r = 0.82$ cross-perplexity correlation), while instruction-format transfers (FiQA $\leftrightarrow$ FinGPT $\leftrightarrow$ Alpaca) achieved moderate correlation ($r = 0.68$–0.73). Cross-format transfer failed: document-pretrained models achieved 2–3$\times$ worse perplexity on instruction tasks (and vice versa) despite shared financial vocabulary.

Domain transfer proved asymmetric: financial pretraining enabled reasonable general-domain performance (WikiText perplexity competitive with specialized general-domain models), but general pretraining failed catastrophically for financial tasks (WikiText pretraining: 48.7 mean financial ppl vs 21.55 for Mixed Financial). This asymmetry reflects vocabulary coverage—financial text includes substantial general vocabulary, but general corpora lack domain-specific terminology (EBITDA, prospectus, liquidity ratios).

These findings suggest **practitioners should prioritize format diversity over domain purity** when curating pretraining mixtures. A mixture spanning documents, dialogues, and Q&A formats within the financial domain generalizes better than narrow focus on a single format, even with larger data volume. Cross-dataset comparison tables provide striking visual evidence: Tables 4.12 and 4.13 show boldface clustering along the News-SEC diagonal (long-form transfer), Tables 4.14 to 4.16 exhibit diagonal boldface patterns plus adjacency (instruction-format clustering), while Table 4.17 shows complete isolation (boldface only in Twitter's own column).

6.1.5 Model Size Selection for Resource-Constrained Settings

We demonstrated that **1.7B models offer optimal performance-efficiency balance**, achieving 92% of 4B's performance (24.12 vs 21.55 ppl on Mixed Financial) while requiring 50% memory (10GB

vs 20GB) and 50% training time (12 vs 24 hours for 100M tokens on Lambda Labs GPUs). This finding directly addresses the thesis motivation of developing lightweight, privacy-preserving models for on-device deployment.

0.6B models remain viable for rapid prototyping and extremely resource-constrained scenarios (mobile devices), accepting 22% performance degradation (27.84 ppl) for 3× faster training. 4B models justify their cost only when maximizing absolute performance is critical and hyperparameter tuning expertise is available—improper learning rate selection at this scale causes training collapse, making 4B models less stable than smaller alternatives.

For the privacy-preserving financial chatbot application motivating this thesis, **1.7B represents the recommended deployment target**: small enough for laptop inference on consumer hardware, large enough for acceptable performance, and stable enough for reliable training without extensive hyperparameter search.

6.1.6 Open-Source Reproducible Pipeline

Beyond empirical findings, we delivered a production-ready training pipeline supporting 26 datasets (10 financial classification, 11 generative Q&A, 5 pretraining corpora), multiple model architectures (Qwen, LLaMA, Gemma, Phi), and advanced techniques (LoRA, FlashAttention, MOE support). The pipeline includes automatic experiment naming, TensorBoard logging, checkpoint management, and comprehensive documentation, lowering barriers to entry for researchers and practitioners.

All experiments in this thesis are fully reproducible using documented commands and publicly available datasets. The codebase has been structured for extensibility—adding new datasets requires minimal modifications (label mappings, prompt templates). This contribution addresses reproducibility challenges in NLP research and provides a foundation for future work in specialized domain adaptation.

6.2 Implications for Practice and Research

6.2.1 For Practitioners: Actionable Deployment Guidelines

Financial institutions and fintech companies developing on-premise NLP systems can directly apply our findings:

Data Strategy: Curate diverse in-domain mixtures (aim for 100M+ tokens across multiple formats) rather than attempting to acquire massive single-format datasets. Prioritize format diversity (documents + Q&A + dialogue) over volume. Use 50cap or similar strategies to prevent dominance. Avoid general-domain corpora (WikiText, C4) unless explicitly required for hybrid applications.

Model Selection: Deploy 1.7B models for production applications balancing quality and resources. Use 0.6B for prototyping and testing. Reserve 4B for scenarios where performance justifies cost and expertise for careful LR tuning is available.

Training Configuration: Use LR=2e-5 for main runs; if a larger model shows instability on a dataset, try a smaller LR (e.g., 1×10^{-5} or 5×10^{-6}). Monitor loss curves to detect instability. Allocate 100M token budgets—diminishing returns beyond this threshold for sub-5B models. Use standard configurations (AdamW, cosine schedules, 1000 warmup steps) which proved stable across experiments.

Privacy and Compliance: On-device deployment with 1.7B models enables GDPR-compliant financial NLP without data transmission to external services—critical for banks, investment firms, and financial advisors handling sensitive client information.

6.2.2 For Researchers: Open Questions and Methodological Lessons

Our work highlights underexplored areas in LM scaling research:

Hyperparameter Sensitivity: Scaling laws literature (**kaplan2020scaling**; **hoffmann2022training**) focuses on compute-optimal training but provides limited guidance for hyperparameter transfer across scales. We did not develop or test a learning-rate scaling theory. Future work should investigate when simple LR reductions help, and explore principled relationships for batch size, warmup steps, weight decay, and optimizer hyperparameters.

Domain Adaptation Theory: Why does format dominate vocabulary for transfer? Our findings challenge intuitions about domain similarity. Theoretical frameworks explaining when syntactic structure (format) versus semantic content (vocabulary) drives generalization would inform curriculum design and transfer learning strategies. Neuroscience-inspired probing of intermediate representations may reveal whether format information resides in different layers/attention heads than vocabulary.

Data Mixing Algorithms: We used static 50cap throughout. Dynamic strategies (DoReMi, temperature sampling, curriculum learning) that adjust mixture weights based on validation loss or task difficulty may outperform static mixing. Ablation studies varying cap thresholds (30%, 40%, 60%) would clarify sensitivity. Meta-learning approaches that optimize mixture ratios as hyperparameters represent promising future directions.

Evaluation Methodology: We assessed pretraining quality via perplexity on held-out test sets. Downstream task evaluation (sentiment classification accuracy, Q&A F1, summarization ROUGE) would validate that pretraining improvements transfer to practical applications. Establishing correlations between pretraining perplexity and downstream performance across diverse tasks would enable efficient model selection without exhaustive downstream evaluation.

6.2.3 For Industry: Privacy-Preserving Financial AI

This work directly addresses emerging regulatory and business needs:

Regulatory Compliance: GDPR, CCPA, and emerging AI regulations increasingly prohibit or restrict transmission of financial data to external APIs (OpenAI, Anthropic). On-device models trained using our methods enable compliant NLP for document analysis, risk assessment, and customer service without data exfiltration.

Competitive Differentiation: Financial institutions accumulating proprietary datasets (transaction records, analyst reports, client communications) can use specialized pretraining to develop competitive advantages—custom models trained on confidential data without exposing information to vendors.

Cost Efficiency: Cloud API costs for LLM inference ($\$0.002 - 0.03$ per 1K tokens for GPT-4 class models) accumulate rapidly at scale. On-premise 1.7B models reduce marginal costs to negligible levels (electricity, amortized hardware), enabling aggressive deployment for high-volume applications (transaction categorization, automated report generation).

Latency and Reliability: Local inference eliminates network latency and dependency on external

service availability—critical for real-time trading applications and customer-facing systems requiring ¡100ms response times.

6.3 Future Research Directions

6.3.1 Scaling to Larger Models and Architectures

Our experiments covered 0.6B-4B parameters (6.7× range) on Qwen3 architecture exclusively. Critical open questions:

Larger Scales: Do 7B, 13B, 70B models exhibit the same mixture effects and similar sensitivity to optimization settings? Larger models may benefit more from diverse pretraining (improved few-shot generalization) or less (stronger preexisting representations). Understanding learning-rate behavior at these scales requires focused empirical and theoretical work.

Architectural Diversity: LLaMA, Gemma, Mistral, Phi use different architectural choices (grouped-query attention variants, different activation functions, rotary embeddings). Validating our findings across architectures would establish generality. Encoder-decoder models (T5, BART) and encoder-only models (BERT, RoBERTa) may show different mixture effects due to bidirectional attention or different pretraining objectives (masked language modeling vs causal).

MOE Architectures: Mixture-of-Experts models (Mixtral, DeepSeek-MOE) offer computational efficiency through sparse activation. Do MOE models benefit more from data mixtures (experts specializing on subdomains) or less (already mixture-like internally)? MOE-specific mixture strategies matching expert count to dataset count represent unexplored territory.

6.3.2 Advanced Mixture Optimization

Our 50cap strategy worked well but wasn't rigorously optimized. Future work should explore:

Dynamic Mixture Schedules: Curriculum learning approaches that shift mixture composition during training—start with general data for basic capabilities, transition to specialized data for domain expertise. Or reverse: start specialized to establish domain vocabulary, add general data to improve consistency.

Adaptive Weighting: Use validation loss gradients or uncertainty estimates to identify which datasets currently contribute most to learning. Upweight informative datasets, downweight exhausted sources. DoReMi (**xie2023doremi**) provides reference implementation; adaptation to specialized domains requires experimentation.

Mixture Ablations: Systematically vary cap threshold (30%, 40%, 50%, 60%, 70%) and measure sensitivity. Optimal threshold may depend on dataset size distribution—highly imbalanced mixtures (one dataset 90% of total) may require aggressive capping, while balanced mixtures may prefer minimal intervention.

Multi-Stage Mixing: Train separate models on individual datasets, then merge via model averaging, task arithmetic, or TIES merging. Compare to simultaneous mixture training. Sequential training (pretrain on Dataset A, continue on Dataset B) versus concurrent mixing represents underexplored design space.

6.3.3 Comprehensive Downstream Evaluation

This thesis assessed pretraining quality via perplexity. Validation on downstream applications would strengthen practical relevance:

Financial Sentiment Analysis: FPB, FiQA-SA, Twitter Financial sentiment datasets. Compare finetuning performance from different pretrained checkpoints (Mixed Financial vs WikiText vs single-dataset). Measure few-shot and zero-shot transfer.

Financial Q&A: FinQA, ConvFinQA, Alpaca-Finance benchmarks. Assess both extractive (span selection) and generative (free-form answer) settings. Evaluate factual accuracy and hallucination rates—critical for financial applications.

Document Summarization: SEC filing summarization, earnings call summarization. Metrics: ROUGE, BERTScore, human evaluation for factuality and conciseness. Privacy-preserving summarization represents high-value application for on-device models.

Long-Context Understanding: Financial documents often exceed 10K tokens (10-K filings, prospectuses). Evaluate long-context capabilities using retrieval-augmented generation or extended-context versions of Qwen3 (32K+ tokens). Does mixture pretraining improve long-document coherence?

6.3.4 Multi-Stage Pretraining Strategies

Our single-stage approach (pretrain directly on financial mixtures) represents one point in a broader design space:

General → Domain Adaptation: Pretrain on WikiText or C4 for general capabilities, then continue pretraining on financial data. Compare to direct financial pretraining. Theory suggests general stage builds strong syntax/reasoning, domain stage adds specialized vocabulary—empirical validation needed.

Domain → Task Specialization: Pretrain on broad financial mixture, then continue on task-specific data (e.g., only sentiment data for sentiment model). Balances general financial knowledge with task-specific optimization.

Mixture Schedules: Gradually shift mixture composition across training—start balanced, progressively upweight high-priority datasets. Or inverse: start specialized, progressively diversify to improve consistency.

Optimal strategies likely depend on target application and available data. Practitioners need decision frameworks: "If you have 10M domain tokens and 100M general tokens, use Strategy X; if 100M domain and 10M general, use Strategy Y."

6.3.5 Open Questions

We did not study learning-rate theory or its interaction with model size and batch size. Understanding when simple LR reductions help—and when they do not—remains open work, alongside broader questions on mixture schedules and transfer to downstream tasks.

6.4 Closing Remarks

This thesis demonstrates that effective specialized language models can be developed without massive computational resources or proprietary datasets. By carefully curating diverse in-domain data mixtures, selecting stable training settings, and targeting lightweight 1–2B parameter models, practitioners can train privacy-preserving financial NLP systems suitable for on-device deployment. In practice, that is the main benefit.

The core insight—that diverse in-domain mixing dramatically outperforms general-domain pretraining for specialized applications—challenges prevalent assumptions favoring general-purpose foundation models. For domains with sufficient available data (finance, legal, medical, scientific), specialized pretraining offers superior performance at lower cost compared to adapting general-purpose models via finetuning or prompting.

As privacy regulations tighten and organizations recognize competitive value in proprietary data, on-device specialized models will become increasingly important. This work provides empirical foundations and practical guidelines for developing such systems, contributing to a future where powerful NLP capabilities are accessible without sacrificing privacy, incurring ongoing API costs, or depending on external service providers.

The open-source pipeline and reproducible experimental methodology lower barriers to entry, enabling researchers and practitioners to build on these findings and extend them to new domains, architectures, and applications. By sharing not just results but complete implementations, we hope to accelerate progress toward privacy-preserving, efficient, and democratically accessible language understanding for specialized domains.

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