Slightly adjusted version for publication

Risk-adjusted performance of CLOs: Impact of industry expertise

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1st of June 2026

under the supervision of

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A thesis submitted for the degree of

Master in International Finance

HEC Paris

Keywords: CLO, industry expertise, leveraged loans, active management, distressed credit

We are grateful to Professor Quirin Fleckenstein for his valuable guidance, constructive feedback, and support throughout this research project. In preparing this thesis, large language models were used. For instance, to enhance the readability, such as for language clarity and correct spelling and grammatical errors.

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Boris Petrov and Nico Fischer

Abstract

This thesis studies whether industry-specific expertise improves the risk-adjusted performance of CLO managers. Using U.S. CLO secondary-market loan trades from 2009 to 2020, it tests whether managers perform better in industries where they have accumulated more prior experience. Expertise is measured using prior same-industry trades and previous-month industry holdings share. The results provide no robust evidence that industry expertise improves abnormal returns or reduces downside risk. The findings are similar across return horizons, transaction types, riskier loan segments, and the holdings-based proxy. Industry-specific trading history does not translate into systematic transaction-level outperformance.

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1. Introduction

Collateralized loan obligations (CLO) managers are among the most important institutional investors in the U.S. leveraged loan market. They buy diversified portfolios of leveraged loans and finance these portfolios by issuing tranches of debt and equity with different levels of seniority. Unlike passive securitizations, CLOs are actively managed vehicles. During the reinvestment period, managers buy, sell, and monitor loans while satisfying portfolio constraints related to diversification, ratings, spreads, and credit quality (Cordell, Roberts and Schwert, 2023). This active management role makes CLOs a useful setting for studying whether professional credit managers add value through their trading decisions.

The question of CLO manager skill is important but difficult to answer at the portfolio level. CLO performance reflects not only the manager's investment decisions, but also leverage, liability structure, collateral composition, market-wide credit conditions, and the contractual constraints of the vehicle. Recent evidence on CLO performance similarly shows that aggregate returns are shaped by vehicle structure, collateral composition, and market conditions, making the separate role of manager skill difficult to isolate from portfolio-level performance (Cordell, Roberts and Schwert, 2023). This problem is related to a broader issue in the active-management literature: even if some managers are skilled, their skill may be hard to observe in aggregate returns. Berk and Green (2004) argue that skilled managers attract capital until the return advantage is competed away, making skill difficult to identify from fund-level performance alone.

This thesis takes a transaction-level approach. Rather than asking whether an entire CLO vehicle outperforms, it asks whether individual loan trades perform better when the manager has more experience in the traded loan's industry. This approach brings the analysis closer to the actual decision made by the manager. Each transaction records what the manager bought or sold, when the trade occurred, and at what price. If industry-specific expertise improves CLO trading decisions, it may therefore be visible in the abnormal returns earned on individual loan transactions.

The motivation for focusing on industry expertise is grounded in the literature on specialisation and industry concentration. Kacperczyk, Sialm and Zheng (2005) show that equity mutual funds with more concentrated industry portfolios outperform more diversified funds, and that this outperformance is concentrated in the industries the funds overweight. Their interpretation is that industry concentration reflects informational advantage: managers concentrate in industries where they have superior knowledge and are therefore better able to select securities. Van Nieuwerburgh and Veldkamp (2009, 2010) provide a theoretical foundation for this idea. In their models, information acquisition is costly and can exhibit increasing returns to specialisation, making it optimal for investors to focus attention on a smaller set of assets or sectors.

Whether this specialisation premium carries over to CLO managers is not obvious. On the one hand, the leveraged loan market may be a setting where industry knowledge is valuable. Loans are less transparent than public equities, trade over the counter, and depend heavily on borrower-specific credit information. Managers who repeatedly trade loans in the same industry may develop useful knowledge through analyst coverage, borrower relationships, and repeated exposure to industry credit cycles. On the other hand, CLO managers operate under portfolio constraints that may limit their ability to exploit industry-specific information. In addition, the secondary loan market may be competitive enough that repeated industry trading does not translate into measurable abnormal performance. This makes the effect of industry expertise an empirical question.

This thesis tests five hypotheses concerning the role of industry expertise in loan trading performance. The central question (H1) is whether managers earn higher abnormal returns when trading loans in industries where they have accumulated prior experience. Building on this, the second hypothesis (H2) examines whether such an expertise advantage is more pronounced for purchases than for sales, a distinction that matters because purchases reflect the active selection of new exposures rather than the unwinding of existing ones. The analysis then shifts to loan risk (H3), examining whether industry knowledge proves especially valuable when trading riskier instruments, where private credit analysis may carry greater weight. A related but distinct question (H4) concerns the depth of a manager's industry focus, specifically whether stronger performance emerges in sectors that account for a larger share of their historical trading activity. Finally, hypothesis 5 (H5) asks whether expertise does more than boost returns, examining whether it also provides a degree of downside protection by reducing both the likelihood and severity of negative actual returns.

The empirical analysis uses a transaction-level panel of U.S. CLO secondary-market loan trades from January 2009 to December 2020, a period long enough to capture variation across both favourable and adverse economic conditions, including the aftermath of the 2008 financial crisis and the onset of the COVID-19 shock in early 2020. The main measure of industry expertise is the log number of previous transactions executed by the same manager in the same Moody’s industry before the current trade. This measure captures accumulated manager-industry experience while remaining strictly backward-looking. As an alternative proxy, the analysis also uses the manager’s previous-month industry holdings share, which captures current portfolio exposure to the transaction industry. Performance is measured using manager-perspective abnormal returns over two- and three-month forward horizons. Figure 10 in the Appendix shows how mean expertise evolves over the sample period, reflecting the mechanical accumulation of transaction history.

The main regression includes manager fixed effects and industry-month fixed effects. Manager fixed effects absorb persistent differences across managers, such as investment style, risk appetite, platform quality, or general skill. Industry-month fixed effects absorb sector-level shocks and market conditions common to loans in the same industry and month. The regressions also control for transaction price, log transaction volume, average spread, rating score, purchase direction, and general manager experience. Standard errors are clustered at the manager level. The main specifications are also re-estimated on a post-2010 sample to ensure that the results are not driven by the early years of the dataset, when observed prior experience is mechanically lower.

The results provide no robust evidence that industry expertise improves CLO managers' transaction-level performance. In the baseline specification, prior industry experience is negative but statistically insignificant at both return horizons. The result is unchanged in the post-2010 sample and when expertise is measured using previous-month industry holdings share. The additional tests also do not support the predicted mechanisms. Industry expertise does not improve performance on purchases, does not become more valuable for riskier loans, and does not predict higher abnormal returns in industries where managers are more concentrated. The downside-risk tests provide no robust evidence that prior industry experience reduces the probability or severity of losses.

The thesis contributes to the literature in three ways. First, it extends the industry-specialisation framework of Kacperczyk, Sialm and Zheng (2005) from equity mutual funds to the CLO secondary loan market. The results suggest that the industry-concentration premium documented in equity funds does not generalise to this setting. Second, it studies manager skill at the transaction level rather than at the vehicle level, allowing the analysis to focus directly on individual trading decisions. Third, it compares two complementary measures of industry expertise: accumulated prior trading experience and previous-month industry holdings share. Across both measures, the evidence points to the same conclusion: industry-specific experience does not generate robust transaction-level outperformance.

The remainder of the thesis proceeds as follows. Chapter 2 reviews the literature on active management, industry specialisation, and information acquisition. Chapter 3 then describes the data and explains how the main variables are constructed. The empirical methodology is laid out in Chapter 4, while Chapter 5 presents and interprets the results. Chapter 6 concludes.

2. Literature Review

Three strands of the literature motivate this study. The first is the broad literature on active management, which asks whether professional money managers actually add value. The starting point is the classic empirical finding that, on average, active mutual fund managers do not generate positive risk-adjusted abnormal performance after costs (Jensen, 1968). Berk and Green (2004) offer an influential explanation for why this can be true even if some managers are genuinely skilled. In their model, investors recognise skill and direct new capital toward skilled managers; because a larger fund is harder to manage profitably, the manager's ability to generate abnormal returns is diluted as assets grow, until the net abnormal return that investors earn is competed back down to zero. The practical lesson is that skill can be real yet difficult to observe in fund-level returns, because those returns reflect the equilibrium between skill and the size of the capital chasing it. This has a direct implication for the present study: one useful place to look for managerial skill is not only the aggregate return of the vehicle, but also the performance of individual trading decisions. By analysing the abnormal return on each loan a manager trades, this thesis tests for skill closer to the decision level, where industry-specific information should be more directly reflected if it affects performance.

The second strand concerns industry specialisation as a source of managerial skill. The most directly relevant study is Kacperczyk, Sialm and Zheng (2005), who examine industry concentration in equity mutual funds. They construct a measure of how far a fund's industry weights deviate from the market portfolio. Funds that deviate more, meaning those that concentrate their holdings in fewer industries, earn higher risk-adjusted returns than diversified ones, by roughly one to two percentage points per year. Importantly, this outperformance is not random: it is concentrated in the exact industries the fund overweights, suggesting that specialisation reflects genuine informational advantage rather than luck. Their interpretation is that managers choose to concentrate where they have an informational advantage: a manager who understands a particular industry well will both hold more of it and trade it more successfully. A similar logic may apply to CLO managers, who specialise in corporate credit and repeatedly trade loans from the same industries. If repeated trading in an industry builds useful, industry-specific knowledge, then a manager should earn higher abnormal returns on loans from industries it has traded often than on loans from industries it rarely touches. Testing whether this industry-concentration premium carries over from equity mutual funds to the CLO secondary loan market is the central question of this thesis. Related evidence from syndicated loan portfolios also suggests that professional investment managers may differ in skill, but that identifying this skill requires looking carefully at the level at which investment decisions are made (Liebscher and Mählmann, 2017).

The third strand supplies the theoretical foundation for why specialisation might pay. Van Nieuwerburgh and Veldkamp (2009, 2010) model the decision of how to allocate limited attention across assets. In their framework, acquiring information is costly but exhibits increasing returns to scale: once an investor has paid the fixed cost of learning about an asset or sector, each additional piece of information about it is cheaper to obtain. This makes specialisation optimal. Rather than learning a little about many assets, an investor may do better by acquiring deep knowledge about a smaller set of assets. Specialised investors then hold more precise beliefs about their chosen assets than the market does, and they can earn excess returns where that informational edge is largest. In a credit setting, this suggests that expertise should matter most for riskier loans, where outcomes depend more heavily on borrower-specific information that may not be fully reflected in prices.

Taken together, these three strands create a clear empirical question. The specialisation literature and the information-acquisition theory predict that industry expertise can generate a performance premium, potentially larger for active purchase decisions and for riskier loans. At the same time, the active-management literature cautions that such premia may be difficult to detect in competitive markets. The CLO secondary market is a useful setting in which to test these predictions because it combines active trading with observable transaction-level data and a natural definition of industry expertise: the industries in which a manager has traded before. This thesis tests whether CLO managers perform better when trading loans in industries where they have accumulated more prior experience.

3. Data

This section describes the transaction-level dataset, the construction of the main variables, and the sample used in the empirical analysis. The analysis uses individual CLO loan transactions, measures performance over two forward return windows, and relates this performance to the manager's prior experience in the industry of the traded loan.

The analysis is based on a transaction-level panel of U.S. collateralized loan obligation managers covering January 2009 through December 2020. The transaction and holdings data are obtained from Creditflux, which provides CLO-level information on loan transactions, portfolio holdings, and related loan characteristics. The unit of observation is a single secondary-market transaction in a leveraged loan. For each transaction, the dataset records the CLO manager executing the trade, the CLO vehicle in which the trade is booked, the issuer of the underlying loan, the trade date, the transaction price, the transaction direction, the U.S. dollar transaction volume, the loan tranche type, the loan's Moody's industry classification, its rating on an ordinal scale, and its average spread. The dataset also contains forward loan returns at two- and three-month horizons, both in actual and benchmark-adjusted form. The sample period is well suited to the study of CLO manager behaviour because it covers the post-crisis expansion of the CLO market and includes both normal market conditions and periods of stress, including the COVID-19 shock in 2020. Figure 6 in the Appendix plots the monthly transaction count and mean abnormal return over the full sample period.

The starting dataset contains secondary-market U.S. CLO loan transactions. The dataset is cleaned by removing duplicate observations, keeping standard loan transactions with the information needed for the empirical tests, and constructing the date and identifier variables used throughout the analysis. The final cleaned transaction-level dataset contains 668,886 observations. Because the empirical specifications require different dependent variables and controls, the number of observations varies across regressions. The abnormal-return regressions use the subset for which the forward abnormal return and all required control variables are available. This gives 447,745 observations for the two-month abnormal-return horizon and 443,372 observations for the three-month horizon in the baseline specification. The downside-risk tests use actual forward returns rather than abnormal returns and therefore have larger samples, with 652,390 observations for the two-month horizon and 643,888 observations for the three-month horizon. Table 1 in the Appendix reports descriptive statistics for the main dependent variables, expertise measures, and transaction-level controls.

The main dependent variable is the forward abnormal return on the traded loan. The two-month abnormal return, denoted abret_f2_w, is the loan's two-month forward return net of a benchmark return for comparable loans in the same Moody's industry. The three-month abnormal return, abret_f3_w, is constructed in the same way and is used as a parallel horizon. Using abnormal returns rather than raw returns is important because CLO managers trade loans across different industries and market conditions. A raw return could reflect broad movements in a sector, whereas the abnormal return is intended to capture the part of performance more closely linked to the individual trading decision.

Returns are measured from the manager's perspective. For purchases, a positive subsequent return represents a gain to the manager, so purchase returns are left unchanged. For sales, the interpretation is reversed: a manager benefits when the sold loan subsequently falls in value, because selling before a decline is a successful trading decision. Sale returns are therefore multiplied by minus one before winsorization, so that positive values consistently represent favourable outcomes for the manager. This adjustment is applied to both actual and abnormal returns. The return variables are then winsorised at the first and ninety-ninth percentiles to reduce the influence of extreme observations. For the downside-risk tests, actual returns are used to construct an indicator for negative manager-perspective returns and a loss-severity variable equal to the absolute value of negative returns and zero otherwise. Figure 1 in the Appendix shows the distributions of the two-month abnormal return and the expertise measure across the full sample.

The main explanatory variable is prior industry experience. For each transaction, the number of previous transactions executed by the same manager in the same Moody's industry before the current trade date is counted. The main measure is the natural logarithm of one plus this cumulative prior trade count. The measure is backward-looking by construction, so it uses only information available before the trade and is not affected by the outcome of the current transaction. It captures the approach that managers may accumulate industry-specific knowledge through repeated trading, analyst coverage, borrower relationships, and familiarity with the credit dynamics of a sector.

Additionally, two complementary measures of industry expertise are used. The first is industry concentration, defined as the share of a manager's previous transactions that occurred in the same Moody's industry as the current trade. This measure captures the relative importance of the industry within the manager's own trading history, rather than the absolute number of prior trades. It is used to test whether managers who are more concentrated in a given industry perform better when trading loans in that industry. The second complementary measure is previous-month industry holdings share. This variable measures the fraction of the manager's portfolio invested in the loan's Moody's industry in the month before the transaction. Unlike the cumulative prior-trades measure, the holdings-based measure captures the manager's current exposure to the industry. It is used as an alternative proxy for industry expertise and is merged into the transaction-level dataset using the previous month's holdings. Figure 8 in the Appendix shows the distributions of industry concentration and general manager experience across the sample.

The regressions include a standard set of transaction-level controls. These are the transaction price, the log of transaction volume, the loan's average spread, the rating score, and a purchase dummy equal to one for purchases and zero for sales. The rating score controls for credit quality, with higher values corresponding to weaker ratings. The average spread captures compensation for credit risk, while transaction price helps account for the fact that loans trading at lower prices may have different expected return dynamics. Transaction volume controls for trade size, and the purchase dummy captures systematic differences between purchase and sale transactions. In the main prior-trades specifications, general manager experience is controlled for, measured as the log number of previous transactions executed by the same manager across all industries. This separates industry-specific experience from the manager's overall activity and scale.

The structure of the sample is uneven across managers, industries, and time: some managers trade much more frequently than others, some industries are more active than others, and transaction volume increases over the sample period as the CLO market grows. These features are important for interpreting the data and motivate the fixed-effects structure described in the next section.

The final dataset therefore provides a detailed transaction-level view of CLO managers' trading behaviour. It allows to compare how managers perform when trading loans in industries where they have more versus less prior experience, while controlling for loan characteristics, manager scale, and industry-time conditions. The next section sets out the regression framework used to conduct this comparison.

4. Methodology

The empirical analysis is conducted at the transaction level. Each observation is a secondary-market loan trade executed by a CLO manager. This structure allows to test whether managers perform better when trading loans in industries where they have accumulated more prior experience. Instead of evaluating the overall performance of a CLO vehicle, the analysis focuses on the performance of individual trading decisions.

The main dependent variable is the manager-perspective abnormal return on the traded loan. The two-month abnormal return is used as the main performance measure, and the three-month abnormal return is used as a parallel horizon. Using two horizons reduces the risk that the results depend on a single return window. The abnormal return measures performance relative to comparable loans in the same industry, while the manager-perspective construction ensures that purchases and sales are evaluated according to whether the trade subsequently benefited the manager.

The baseline specification estimates the following fixed-effects regression:

$$AR_{i,m,j,t} = \alpha + \beta\, Expertise_{m,j,t-1} + \gamma' X_{i,m,j,t} + \mu_m + \lambda_{j,t} + \varepsilon_{i,m,j,t} \qquad (1)$$

In Equation (1), $AR_{i,m,j,t}$ is the forward abnormal return on transaction i, executed by manager m, in industry j, at time t. The main explanatory variable, $Expertise_{m,j,t-1}$ is the log number of previous transactions executed by manager m in industry j before the current trade. The coefficient of interest is β. A positive and statistically significant estimate would indicate that prior industry experience is associated with higher abnormal returns.

The vector $X_{i,m,j,t}$ contains transaction-level controls. These include transaction price, log transaction volume, average spread, rating score, a purchase dummy, and general manager experience. Transaction price, spread, and rating control for differences in loan characteristics and credit risk. Transaction volume accounts for trade size. The purchase dummy controls for systematic differences between purchases and sales. General manager experience is included to separate industry-specific experience from the manager's overall trading activity across all industries.

The regression includes manager fixed effects, μ_m, and industry-month fixed effects, $\lambda_{j,t}$. Fixed-effects models are commonly used in panel settings to absorb unobserved heterogeneity that is constant within a group, such as persistent manager characteristics or industry-month conditions (Wooldridge, 2010, pp. 265–274). In this setting, manager fixed effects absorb persistent differences across CLO managers, such as investment style, risk appetite, platform quality, or general skill. Industry-month fixed effects absorb shocks common to loans in the same industry and month, such as sector-level news, changes in credit conditions, or shifts in demand for loans in that industry. Identification therefore derives from within-industry-month variation in manager experience, while controlling for persistent differences across managers.

Standard errors are clustered at the manager level. This allows for correlation across the many transactions executed by the same manager and avoids treating repeated trades by one manager as independent observations. This follows the standard concern in finance panel data that standard errors can be understated when residuals are correlated within firms, funds, or other repeated observational units (Petersen, 2009).

The remaining empirical tests are estimated as extensions of the baseline specification. The interaction specifications add the relevant interaction terms to the same regression framework, while the concentration specification replaces the prior-trade-count measure with the manager’s prior industry concentration. The downside-risk specifications use the same control structure and fixed effects but replace abnormal returns with actual-return-based downside measures. Two downside measures are used because downside risk has both an extensive and an intensive margin: whether a loss occurs, and how large the loss is when it occurs.

The analysis also uses the manager’s previous-month industry holdings share as an alternative expertise proxy. This measure captures current exposure to the industry rather than cumulative trading history. Re-estimating the main tests with this holdings-based proxy helps assess whether the results depend on the specific definition of industry expertise.

The robustness checks focus on two dimensions. First, all main specifications are estimated at both two- and three-month forward horizons. Second, the regressions are re-estimated on a post-2010 sample, which excludes transactions from 2009 and 2010 while still using those years to construct prior experience variables. This addresses the concern that the expertise measure is mechanically low at the beginning of the sample because prior transactions are only observed from 2009 onward. Together, these checks test whether the results are sensitive to the return horizon or to the early sample period.

5. Results

This section presents the empirical results for the five hypotheses, forming the core of the thesis. The main analysis uses manager fixed effects and industry-month fixed effects, with standard errors clustered at the manager level. For each hypothesis, the results first focus on the prior-trade-count measure of industry expertise. The post-2010 specification is then used to check whether the result is driven by the early years of the sample, when prior experience is mechanically lower because transaction history is only observed from 2009 onward. Where relevant, the holdings-based proxy is used as an additional check, measuring expertise as the manager's previous-month portfolio share in the transaction industry. All tables are located in the Appendix.

Before turning to the fixed-effects regressions, the raw sorting results provide a simple descriptive benchmark. Sorting transactions by prior industry experience does not show a positive relationship between expertise and abnormal returns. At the margin, higher-expertise trades have slightly lower average abnormal returns than lower-expertise trades. However, these sorts do not control for manager characteristics, transaction characteristics, or industry-month conditions. The fixed-effects regressions therefore provide the main tests of the hypotheses. Figure 2 in the Appendix shows mean abnormal returns by within-month expertise quintile as a descriptive illustration.

5.1. Industry expertise and abnormal returns

Table 2 reports the baseline fixed-effects regressions testing whether prior industry experience is associated with higher abnormal returns. The coefficient on prior industry experience is negative in both return horizons, but statistically insignificant. In the two-month specification, the coefficient is -0.0004. In the three-month specification, the coefficient is -0.0005. These estimates provide no evidence that CLO managers earn higher abnormal returns when trading loans in industries where they have accumulated more prior transaction experience.

The result is also economically small. The coefficient is close to zero relative to the scale of abnormal returns, suggesting that even large differences in prior industry trading history are not associated with meaningful differences in subsequent risk-adjusted performance. Among the controls, the purchase dummy is positive and statistically significant in both horizons, indicating that purchases are associated with higher manager-perspective abnormal returns than sales. However, the main variable of interest remains statistically insignificant, so the baseline result does not support the prediction that industry expertise improves trade-level performance. Figure 3 in the Appendix presents a binscatter of residualised abnormal returns against residualised expertise, confirming the absence of a positive relationship.

The post-2010 results, reported in columns 2 and 4 of Table 2, are nearly identical: prior industry experience remains negative and statistically insignificant at both horizons. Figure 5 in the Appendix plots the expertise coefficient and its 95% confidence interval across nine alternative specifications, illustrating the robustness of this null result.

The holdings-based proxy also does not support hypothesis H1. Table 7 replaces cumulative prior industry trades with the manager's previous-month industry holdings share. The coefficient on previous-month industry share is again negative and statistically insignificant in both horizons: -0.0072 at the two-month horizon and -0.0118 at the three-month horizon. This indicates that the absence of an expertise premium is not specific to the prior-trade-count measure. Whether expertise is measured by accumulated trading history or by current portfolio exposure to the industry, the results do not show that industry expertise improves abnormal returns.

Overall, hypothesis H1 is not supported. The baseline coefficient is negative but insignificant, the post-2010 robustness check gives the same result, and the holdings-based proxy also fails to produce a positive or significant expertise effect. The evidence therefore suggests that prior industry experience does not translate into systematic transaction-level outperformance in the CLO secondary loan market.

5.2. Purchases versus sales

Table 3 tests whether prior industry experience matters differently for purchases and sales by interacting prior industry experience with the purchase dummy. The interaction term is negative in both horizons. In the two-month specification, the coefficient on the interaction is -0.0006 and statistically significant at the 5% level. In the three-month specification, the coefficient is -0.0005 but statistically insignificant. This means that the effect of prior industry experience is not stronger for purchases. If anything, the coefficient suggests a weaker expertise effect for purchases relative to sales.

The purchase dummy itself is positive and statistically significant in both horizons. It is significant at the 1% level in the two-month specification and at the 5% level in the three-month specification. This indicates that purchases are associated with higher manager-perspective abnormal returns than sales, holding the other controls and fixed effects constant. However, this does not imply that experienced managers perform better on purchases. The relevant test for hypothesis H2 is the interaction between prior industry experience and the purchase dummy, and that coefficient does not support a positive purchase-specific expertise premium. Figure 9 in the Appendix illustrates the difference in mean abnormal returns between purchases and sales.

The post-2010 results, reported in columns 2 and 4 of Table 3, reinforce this interpretation. The interaction remains negative and becomes statistically significant in both horizons: at the 1% level in the two-month specification and at the 5% level in the three-month specification.

The holdings-based proxy provides only weak and inconsistent evidence. Table 8 replaces prior industry trades with previous-month industry holdings share. The interaction between previous-month industry share and the purchase dummy is positive, but it is statistically insignificant at the two-month horizon and only weakly significant at the 10% level at the three-month horizon. Moreover, the result is not consistent across horizons and does not overturn the main prior-trades result.

Overall, hypothesis H2 is not supported. Purchases perform better than sales on average, but there is no evidence that industry expertise makes purchases perform better. The main prior-trades specification shows a negative purchase interaction, and the holdings-based specification provides at most weak and inconsistent evidence in the opposite direction. Figure 4 in the Appendix shows the binscatter of residualised abnormal returns against residualised expertise separately for purchases and sales.

5.3. Riskier loans

Table 4 tests whether prior industry experience matters more for riskier loans. Panel A focuses on high-spread loans, while Panel B focuses on low-rated loans. The prediction is that expertise should be more valuable in riskier loans because these are the cases where borrower-specific information and industry knowledge should matter more.

Panel A does not support this prediction. The interaction between prior industry experience and the high-spread loan indicator is negative in both horizons. In the two-month specification, the coefficient is -0.0005 and statistically significant at the 10% level. In the three-month specification, the coefficient is -0.0007 and statistically significant at the 5% level. This is the opposite of the expected sign. Rather than showing that expertise becomes more valuable in high-spread loans, the estimates suggest that the expertise effect is weaker for these loans.

Panel B provides no evidence that expertise matters more for low-rated loans. The interaction between prior industry experience and the low-rated loan indicator is negative in both horizons, but statistically insignificant. This means that lower credit ratings do not appear to strengthen the relationship between prior industry experience and abnormal returns.

The post-2010 results, reported in columns 2 and 4 of Table 4, are very similar. For high-spread loans, the interaction remains negative and is statistically significant at the 10% level in the two-month specification and at the 5% level in the three-month specification. For low-rated loans, the interaction remains negative but statistically insignificant in both horizons.

The holdings-based results in Table 9 also do not support hypothesis H3. When expertise is measured using previous-month industry holdings share, the high-spread interaction is statistically insignificant in both horizons. The low-rated interaction is also statistically insignificant in both horizons. Therefore, the alternative expertise proxy does not show that expertise is more valuable for riskier loans.

Overall, hypothesis H3 is not supported. The high-spread interaction is negative rather than positive, the low-rated interaction is statistically insignificant, and the holdings-based proxy provides no evidence that industry expertise improves performance in riskier loans. The results therefore do not support the idea that industry expertise is most valuable when informational frictions are likely to be larger. Figure 7 in the Appendix provides a heatmap of mean abnormal returns by rating bucket and expertise quintile.

5.4. Industry concentration

Table 5 tests whether managers perform better when trading in industries that represent a larger share of their prior trading activity. Unlike the baseline prior-trades measure, which captures the absolute number of previous transactions in the same industry, industry concentration captures relative specialisation. A positive coefficient would indicate that managers outperform in industries that are more central to their own trading history.

The results do not support this prediction. The coefficient on industry concentration is negative in both return horizons, but statistically insignificant. In the two-month specification, the coefficient is -0.0048. In the three-month specification, the coefficient is -0.0071. This means that managers do not earn higher abnormal returns in industries that account for a larger share of their previous trading activity.

The post-2010 results, reported in columns 2 and 4 of Table 5, are nearly identical. Industry concentration remains negative and statistically insignificant at both horizons. The coefficients are -0.0038 in the two-month specification and -0.0052 in the three-month specification. This indicates that the result is not driven by the early sample period, when the prior trading history is mechanically shorter.

The holdings-based results are consistent with this interpretation. Although previous-month industry holdings share is not the same measure as prior transaction concentration, it also captures the importance of an industry within the manager’s activity. As shown in Table 7, previous-month industry share is negative and statistically insignificant in both abnormal-return horizons. Therefore, neither prior trading concentration nor current portfolio exposure provides evidence that industry specialisation improves risk-adjusted performance.

Overall, hypothesis H4 is not supported. The results show no evidence that managers with more concentrated prior activity in a given industry perform better when trading loans in that industry. This contrasts with the approach that specialisation should reveal informational advantage in the manager's core industries.

5.5. Downside risk

Table 6 tests whether prior industry experience reduces actual downside risk. Unlike the previous tests, these regressions use actual returns rather than abnormal returns. Panel A examines the probability of a negative actual return, while Panel B examines actual loss severity. This separates whether expertise helps managers avoid losses from whether it helps reduce the size of losses when they occur.

Panel A provides no evidence that prior industry experience reduces the probability of losses. The coefficient on prior industry experience is close to zero and statistically insignificant in both return horizons. In the two-month specification, the coefficient is 0.0001. In the three-month specification, the coefficient is 0.0017. Therefore, more experienced managers are not less likely to experience negative actual returns when trading in industries where they have more prior transaction history.

Panel B gives slightly more favourable but still weak evidence. The coefficient on prior industry experience is negative in both horizons, which is consistent with lower loss severity, but it is statistically insignificant in the baseline specifications. The coefficient is -0.0005 at the two-month horizon and -0.0007 at the three-month horizon. This suggests that prior industry experience may be associated with smaller losses, but the baseline evidence is not strong enough to support a robust conclusion.

The post-2010 results, reported in columns 2 and 4 of Table 6, are similar for the probability of negative actual returns: prior industry experience remains statistically insignificant in both horizons. For actual loss severity, the evidence becomes stronger. The coefficient is -0.0006 in the two-month specification and -0.0008 in the three-month specification, and both are statistically significant at the 10% level. This provides weak evidence that, after excluding the early sample years, prior industry experience is associated with lower loss severity. However, the significance is only marginal, and the result does not extend to the probability of losses.

The holdings-based results in Table 10 do not provide support for hypothesis H5. Previous-month industry share is statistically insignificant in both downside-risk specifications. In Panel A, the coefficient is positive but insignificant for the probability of negative actual returns. In Panel B, the coefficient is negative but insignificant for actual loss severity. Therefore, the holdings-based proxy does not confirm that industry expertise reduces either the frequency or the severity of downside outcomes.

Overall, hypothesis H5 receives only limited support, and only for loss severity in the post-2010 prior-trades specification. The main baseline results do not show that prior industry experience reduces downside risk, and the holdings-based proxy is insignificant throughout. The evidence therefore does not support a robust downside-protection effect from industry expertise.

6. Conclusion

This thesis investigates whether industry expertise improves the transaction-level performance of U.S. CLO managers. Using a panel of secondary-market loan transactions from January 2009 to December 2020, the analysis tests whether managers perform better when trading loans in industries where they have accumulated more prior experience. Performance is measured using two- and three-month forward abnormal returns, and the main empirical design controls for manager fixed effects, industry-month fixed effects, loan characteristics, trade size, transaction direction, and general manager experience.

The results provide no robust evidence of an industry-expertise premium. In the baseline specification, prior industry experience is negative but statistically insignificant at both return horizons. The same conclusion holds in the post-2010 sample, suggesting that the result is not driven by the early years of the dataset when observed prior experience is mechanically lower. The holdings-based proxy leads to the same conclusion: managers do not earn higher abnormal returns when the transaction industry represents a larger share of their previous-month holdings.

The additional tests also fail to support the predicted mechanisms. Industry expertise does not become more valuable for purchases; in the prior-trades specification, the interaction between prior industry experience and the purchase dummy is negative rather than positive. Expertise also does not appear to be more valuable for riskier loans. The high-spread interaction is negative, and the low-rated interaction is statistically insignificant. Industry concentration does not predict higher abnormal returns, and the downside-risk tests provide no robust evidence that prior industry experience reduces the probability or severity of losses. At most, there is weak evidence that prior industry experience is associated with lower loss severity in the post-2010 sample, but this result is not strong enough to change the overall conclusion.

The thesis contributes to the asset-management literature by testing whether the industry-specialisation premium documented in equity mutual funds carries over to the CLO secondary loan market. The evidence suggests that it does not. Repeated trading in an industry and larger current exposure to that industry do not translate into systematic transaction-level outperformance. This indicates that industry-specific trading history is not, by itself, a reliable measure of CLO manager skill.

A possible interpretation is that the CLO secondary loan market is sufficiently competitive for industry-specific information to be reflected in prices, limiting the scope for experienced managers to earn abnormal returns from repeated trading in the same sector. Another possibility is that CLO managers operate under portfolio, rating, diversification, and reinvestment constraints that limit their ability to exploit any informational advantage they may have. In this setting, industry experience may still help managers understand borrowers and manage portfolios, but it does not appear to generate measurable abnormal performance at the transaction level.

From a practical perspective, the results suggest that industry-specific experience alone should not be treated as a reliable reason to pay a premium for a CLO manager or to infer superior trading skill. Investors and allocators may therefore need to look beyond a manager's sector experience or industry concentration when evaluating CLO manager quality. Overall, the findings point to a simple conclusion: in this sample, industry expertise does not robustly explain the risk-adjusted performance of CLO managers' individual loan trades.

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Appendix

Table of Appendices

Table 1: Descriptive statistics

	N	Mean	Std. dev.	P25	Median	P75
Panel A: Return variables						
Two-month abnormal return	448,256	0.0015	0.0265	-0.0053	0.0013	0.0094
Three-month abnormal return	443,878	0.0013	0.0313	-0.0065	0.0016	0.0108
Two-month actual return	668,886	0.0023	0.0441	-0.0094	0.0035	0.0150
Three-month actual return	660,190	0.0026	0.0515	-0.0127	0.0052	0.0188
Panel B: Expertise measures						
Prior industry experience	652,810	5.3347	1.6479	4.3694	5.5294	6.5294
Industry concentration	652,271	0.0671	0.0471	0.0335	0.0564	0.0924
Previous-month industry holdings share	646,803	0.0652	0.0412	0.0319	0.0570	0.0922
General manager experience	668,886	8.2565	1.4911	7.4331	8.4822	9.3836
Panel C: Transaction-level controls						
Transaction price	668,886	97.1158	5.9091	97.2500	99.5000	100.0000
Log transaction volume	668,876	12.8805	1.2547	12.1129	13.0187	13.8078
Average spread	655,102	3.6288	1.1509	2.8396	3.5049	4.3156
Rating score	654,801	13.9944	1.6883	13.0000	14.0000	15.0000
Purchase dummy	668,886	0.5568	0.4968	0.0000	1.0000	1.0000

Notes: This table reports descriptive statistics for the main dependent variables, expertise measures, and transaction-level controls used in the empirical analysis. Abnormal and actual returns are measured from the manager's perspective. Prior industry experience is measured as the log number of previous transactions by the same manager in the same Moody's industry. Industry concentration is the share of the manager's previous transactions in the same industry. Previous-month industry holdings share measures the manager's portfolio exposure to the transaction industry in the month before the trade. General manager experience is measured as the log number of previous transactions by the same manager across all industries. N varies across variables because of missing values in return horizons, holdings data, and transaction-level controls.

Table 2: Baseline fixed-effects regression of abnormal returns

	Baseline f2	Post-2010 f2	Baseline f3	Post-2010 f3
Prior industry experience	-0.0004	-0.0004	-0.0005	-0.0004
	(0.0005)	(0.0005)	(0.0007)	(0.0007)
General manager experience	-0.0009	-0.0011*	-0.0012	-0.0014*
	(0.0006)	(0.0006)	(0.0007)	(0.0007)
Transaction price	-0.0001	-0.0001	-0.0001	-0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log transaction volume	0.0001	0.0001	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Average spread	-0.0002	-0.0002	-0.0002	-0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Rating score	-0.0003*	-0.0003	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Purchase dummy	0.0020***	0.0021***	0.0013***	0.0015***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Constant	0.0212	0.0207	0.0190	0.0190
	(0.0182)	(0.0184)	(0.0205)	(0.0210)
Observations	447,745	442,649	443,372	438,392
R-squared	0.0878	0.0829	0.0877	0.0817

Notes: This table reports estimates from fixed-effects regressions of winsorised abnormal returns on prior industry experience and transaction-level controls. The dependent variables are abret_f2_w and abret_f3_w, representing the two forward abnormal return horizons. Abnormal returns are measured from the manager's perspective: purchase returns are left unchanged, while sale returns are multiplied by -1 before winsorization. Prior industry experience is measured as the log number of previous transactions by the same manager in the same Moody's industry before the current transaction date. General manager experience is measured as the log number of previous transactions by the same manager across all industries. The post-2010 columns exclude transactions from 2009 and 2010 from the regression sample, while still using these years to construct prior experience variables. Standard errors are clustered at the manager level and reported in parentheses. The regressions include manager fixed effects and industry-month fixed effects. Coefficients are measured in decimal values. The stars indicate statistical significance: * 10%, ** 5%, *** 1%.

Table 3: Purchase interaction fixed-effects regression of abnormal returns

	Baseline f2	**Post-2010 f2**	**Baseline f3**	**Post-2010 f3**
Prior industry experience	-0.0000	0.0002	-0.0002	0.0001
	(0.0004)	(0.0004)	(0.0006)	(0.0007)
Purchase dummy	0.0054***	0.0069***	0.0040**	0.0056***
	(0.0014)	(0.0015)	(0.0016)	(0.0016)
Prior industry experience × Purchase dummy	-0.0006**	-0.0008***	-0.0005	-0.0007**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
General manager experience	-0.0008	-0.0010*	-0.0011	-0.0013*
	(0.0006)	(0.0006)	(0.0007)	(0.0007)
Transaction price	-0.0001	-0.0000	-0.0001	-0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log transaction volume	0.0001	0.0001	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Average spread	-0.0002	-0.0002	-0.0002	-0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Rating score	-0.0003*	-0.0003	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	0.0181	0.0164	0.0167	0.0145
	(0.0182)	(0.0184)	(0.0208)	(0.0210)
Marginal effect of prior industry experience for purchases	-0.0006	-0.0007	-0.0006	-0.0007
	(0.0005)	(0.0005)	(0.0007)	(0.0007)
Observations	447,745	442,649	443,372	438,392
R-squared	0.0880	0.0834	0.0878	0.0819

Notes: This table reports estimates from fixed-effects regressions of winsorised abnormal returns on prior industry experience, a purchase dummy, and their interaction. The dependent variables are abret_f2_w and abret_f3_w, representing the two forward abnormal return horizons. Abnormal returns are measured from the manager's perspective: purchase returns are left unchanged, while sale returns are multiplied by -1 before winsorization. Prior industry experience is measured as the log number of previous transactions by the same manager in the same Moody's industry before the current transaction date. General manager experience is measured as the log number of previous transactions by the same manager across all industries. The interaction term tests whether the effect of prior industry experience differs for purchases relative to sales. The marginal effect of prior industry experience for purchases is calculated as the sum of prior industry experience and its interaction with the purchase dummy. The post-2010 columns exclude transactions from 2009 and 2010 from the regression sample, while still using these years to construct prior experience variables. Standard errors are clustered at the manager level and reported in parentheses. The regressions include manager fixed effects and industry-month fixed effects. Coefficients are measured in decimal values. The stars indicate statistical significance: * 10%, ** 5%, *** 1%.

Table 4: Risk interaction fixed-effects regression of abnormal returns

Panel A: High-spread loans

	Baseline f2	Post-2010 f2	Baseline f3	Post-2010 f3
Prior industry experience	-0.0002	-0.0001	-0.0001	-0.0001
	(0.0005)	(0.0005)	(0.0007)	(0.0007)
High-spread loan	0.0038**	0.0038**	0.0051***	0.0050***
	(0.0017)	(0.0018)	(0.0018)	(0.0018)
Prior industry experience × High-spread loan	-0.0005*	-0.0005*	-0.0007**	-0.0007**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
General manager experience	-0.0008	-0.0010*	-0.0011	-0.0013*
	(0.0006)	(0.0006)	(0.0007)	(0.0007)
Transaction price	-0.0001	-0.0001	-0.0001	-0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log transaction volume	0.0001	0.0001	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Average spread	-0.0005	-0.0005	-0.0007	-0.0007
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Rating score	-0.0003*	-0.0003	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Purchase dummy	0.0020***	0.0021***	0.0013***	0.0015***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Constant	0.0200	0.0195	0.0174	0.0165
	(0.0186)	(0.0190)	(0.0209)	(0.0212)
Marginal effect of expertise in high-spread loans	-0.0007	-0.0006	-0.0008	-0.0007
	(0.0005)	(0.0005)	(0.0006)	(0.0007)
Observations	447,745	442,649	443,372	438,392
R-squared	0.0880	0.0832	0.0880	0.0820

Panel B: Low-rated loans

	Baseline f2	Post-2010 f2	Baseline f3	Post-2010 f3
Prior industry experience	-0.0004	-0.0003	-0.0004	-0.0003
	(0.0005)	(0.0005)	(0.0007)	(0.0007)
Low-rated loan	0.0010	0.0012	0.0005	0.0010
	(0.0016)	(0.0017)	(0.0016)	(0.0016)
Prior industry experience × Low-rated loan	-0.0001	-0.0002	-0.0002	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
General manager experience	-0.0009	-0.0011*	-0.0012	-0.0014*
	(0.0006)	(0.0006)	(0.0007)	(0.0007)
Transaction price	-0.0001	-0.0001	-0.0001	-0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log transaction volume	0.0001	0.0001	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Average spread	-0.0001	-0.0002	-0.0003	-0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Rating score	-0.0004	-0.0004	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Purchase dummy	0.0020***	0.0021***	0.0013***	0.0015***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Constant	0.0217	0.0215	0.0161	0.0157
	(0.0189)	(0.0191)	(0.0212)	(0.0215)
Marginal effect of expertise in low-rated loans	-0.0005	-0.0004	-0.0006	-0.0005
	(0.0004)	(0.0004)	(0.0006)	(0.0007)
Observations	447,745	442,649	443,372	438,392
R-squared	0.0878	0.0829	0.0877	0.0817

Notes: This table reports estimates from fixed-effects regressions of winsorised abnormal returns on prior industry experience, loan-risk indicators, and their interaction terms. Panel A tests whether the effect of prior industry experience differs for high-spread loans. Panel B tests whether the effect differs for low-rated loans. The dependent variables are abret_f2_w and abret_f3_w, representing the two forward abnormal return horizons. Abnormal returns are measured from the manager’s perspective:

purchase returns are left unchanged, while sale returns are multiplied by -1 before winsorization. Prior industry experience is measured as the log number of previous transactions by the same manager in the same Moody's industry before the current transaction date. High-spread loans are defined as loans with an average spread above the sample median. Low-rated loans are defined as loans with a rating score strictly above the sample median. The marginal effect of expertise in risky loans is calculated as the sum of prior industry experience and the relevant interaction term. The post-2010 columns exclude transactions from 2009 and 2010 from the regression sample, while still using these years to construct prior experience variables. Standard errors are clustered at the manager level and reported in parentheses. The regressions include manager fixed effects and industry-month fixed effects. Coefficients are measured in decimal values. The stars indicate statistical significance: * 10%, ** 5%, *** 1%.

Table 5: Industry concentration fixed-effects regression of abnormal returns

	Baseline f2	Post-2010 f2	Baseline f3	Post-2010 f3
Industry concentration	-0.0048	-0.0038	-0.0071	-0.0052
	(0.0058)	(0.0062)	(0.0085)	(0.0093)
General manager experience	-0.0013***	-0.0014***	-0.0016***	-0.0018***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Transaction price	-0.0001	-0.0001	-0.0001	-0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log transaction volume	0.0001	0.0001	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Average spread	-0.0002	-0.0002	-0.0002	-0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Rating score	-0.0003*	-0.0003	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Purchase dummy	0.0020***	0.0021***	0.0013***	0.0015***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Constant	0.0224	0.0217	0.0235	0.0220
	(0.0186)	(0.0189)	(0.0209)	(0.0213)
Observations	447,745	442,649	443,372	438,392
R-squared	0.0877	0.0829	0.0877	0.0817

Notes: This table reports estimates from fixed-effects regressions of winsorised abnormal returns on prior industry concentration and transaction-level controls. The dependent variables are abret_f2_w and abret_f3_w, representing the two forward abnormal return horizons. Abnormal returns are measured from the manager's perspective: purchase returns are left unchanged, while sale returns are multiplied by -1 before winsorization. Industry concentration is measured as the share of the manager's previous transactions that occurred in the same Moody's industry as the current transaction. General manager experience is measured as the log number of previous transactions by the same manager across all industries. The post-2010 columns exclude transactions from 2009 and 2010 from the regression sample, while still using these years to construct prior experience variables. Standard errors are clustered at the manager level and reported in parentheses. The regressions include manager fixed effects and industry-month fixed effects. Coefficients are measured in decimal values. The stars indicate statistical significance: * 10%, ** 5%, *** 1%.

Table 6: Fixed-effects regressions of actual downside risk

Panel A: Probability of negative actual returns

	Baseline f2	**Post-2010 f2**	**Baseline f3**	**Post-2010 f3**
Prior industry experience	0.0001	-0.0001	0.0017	0.0015
	(0.0045)	(0.0046)	(0.0044)	(0.0046)
General manager experience	0.0064	0.0074	0.0042	0.0053
	(0.0069)	(0.0071)	(0.0068)	(0.0070)
Transaction price	0.0031***	0.0031***	0.0027***	0.0027***
	(0.0008)	(0.0008)	(0.0009)	(0.0009)
Log transaction volume	0.0069***	0.0072***	0.0060***	0.0062***
	(0.0017)	(0.0017)	(0.0019)	(0.0019)
Average spread	-0.0007	0.0005	-0.0005	0.0005
	(0.0028)	(0.0028)	(0.0029)	(0.0029)
Rating score	0.0007	0.0002	-0.0022	-0.0027
	(0.0020)	(0.0020)	(0.0027)	(0.0027)
Purchase dummy	-0.5298***	-0.5301***	-0.5762***	-0.5759***
	(0.0081)	(0.0083)	(0.0081)	(0.0082)
Constant	0.2849***	0.2760**	0.4069***	0.3994***
	(0.1059)	(0.1082)	(0.1159)	(0.1182)
Observations	652,390	641,519	643,888	633,144
R-squared	0.3506	0.3480	0.4002	0.3972

Panel B: Actual loss severity

	Baseline f2	**Post-2010 f2**	**Baseline f3**	**Post-2010 f3**
Prior industry experience	-0.0005	-0.0006*	-0.0007	-0.0008*
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
General manager experience	0.0009**	0.0010**	0.0011**	0.0013**
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Transaction price	-0.0018***	-0.0018***	-0.0023***	-0.0023***

	Baseline f2	Post-2010 f2	Baseline f3	Post-2010 f3
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log transaction volume	0.0000	0.0001	0.0001	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Average spread	0.0007***	0.0008***	0.0011***	0.0012***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Rating score	0.0007***	0.0007***	0.0009***	0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Purchase dummy	-0.0055***	-0.0054***	-0.0094***	-0.0092***
	(0.0006)	(0.0006)	(0.0008)	(0.0008)
Constant	0.1674***	0.1657***	0.2210***	0.2187***
	(0.0098)	(0.0100)	(0.0113)	(0.0115)
Observations	652,390	641,519	643,888	633,144
R-squared	0.3749	0.3678	0.3955	0.3870

Notes: This table reports estimates from fixed-effects regressions of actual downside risk on prior industry experience and transaction-level controls. Panel A uses negative actual return indicators as dependent variables, equal to one when the winsorised forward actual return is below zero and zero otherwise. Panel B uses actual loss severity as the dependent variable, defined as the absolute value of the negative actual return and zero otherwise. Actual returns are measured from the manager's perspective: purchase returns are left unchanged, while sale returns are multiplied by -1 before winsorization. Prior industry experience is measured as the log number of previous transactions by the same manager in the same Moody's industry before the current transaction date. General manager experience is measured as the log number of previous transactions by the same manager across all industries. The post-2010 columns exclude transactions from 2009 and 2010 from the regression sample, while still using these years to construct prior experience variables. Standard errors are clustered at the manager level and reported in parentheses. The regressions include manager fixed effects and industry-month fixed effects. Coefficients are measured in decimal values. The stars indicate statistical significance: * 10%, ** 5%, *** 1%.

Table 7: Holdings-based fixed-effects regression of abnormal returns

	Baseline f2	**Baseline f3**
Previous-month industry share	-0.0072	-0.0118
	(0.0091)	(0.0111)
Log total previous-month manager holdings	0.0006**	0.0009**
	(0.0003)	(0.0004)
General manager experience	-0.0018***	-0.0023***
	(0.0005)	(0.0006)
Transaction price	-0.0001	-0.0001
	(0.0002)	(0.0002)
Log transaction volume	0.0001	0.0002
	(0.0002)	(0.0002)
Average spread	-0.0002	-0.0003
	(0.0003)	(0.0004)
Rating score	-0.0003*	-0.0001
	(0.0002)	(0.0002)
Purchase dummy	0.0020***	0.0013***
	(0.0004)	(0.0004)
Constant	0.0134	0.0070
	(0.0194)	(0.0219)
Observations	443,900	439,573
R-squared	0.0877	0.0878

Notes: This table reports estimates from fixed-effects regressions of winsorised abnormal returns on previous-month industry share and transaction-level controls. The dependent variables are abret_f2_w and abret_f3_w, representing the two forward abnormal return horizons. Abnormal returns are measured from the manager's perspective: purchase returns are left unchanged, while sale returns are multiplied by -1 before winsorization. Previous-month industry share is measured as the share of the manager's holdings allocated to the transaction industry in the previous month. Log total previous-month manager holdings is included to control for the overall size of the manager's portfolio. General manager experience is measured as the log number of previous transactions by the same manager across all industries. Standard errors are clustered at the manager level and reported in parentheses. The regressions include manager fixed effects and industry-month fixed effects. Coefficients are measured in decimal values. The stars indicate statistical significance: * 10%, ** 5%, *** 1%.

Table 8: Holdings-based purchase interaction fixed-effects regression of abnormal returns

	Baseline f2	**Baseline f3**
Previous-month industry share	-0.0152*	-0.0279**
	(0.0091)	(0.0115)
Purchase dummy	0.0009	-0.0009
	(0.0010)	(0.0013)
Previous-month industry share × Purchase dummy	0.0146	0.0292*
	(0.0128)	(0.0160)
Log total previous-month manager holdings	0.0006**	0.0009**
	(0.0003)	(0.0004)
General manager experience	-0.0018***	-0.0023***
	(0.0005)	(0.0006)
Transaction price	-0.0001	-0.0001
	(0.0002)	(0.0002)
Log transaction volume	0.0001	0.0002
	(0.0002)	(0.0002)
Average spread	-0.0002	-0.0003
	(0.0003)	(0.0004)
Rating score	-0.0003*	-0.0001
	(0.0002)	(0.0002)
Constant	0.0142	0.0085
	(0.0194)	(0.0218)
Marginal effect of industry share for purchases	-0.0007	0.0013
	(0.0125)	(0.0151)
Observations	443,900	439,573
R-squared	0.0879	0.0882

Notes: This table reports estimates from fixed-effects regressions of winsorised abnormal returns on previous-month industry share, a purchase dummy, and their interaction. The dependent variables are abret_f2_w and abret_f3_w, representing the two forward abnormal return horizons. Abnormal returns are measured from the manager's perspective: purchase returns are left unchanged, while sale returns are multiplied by -1 before winsorization. Previous-month industry share is measured as the share of the manager's holdings allocated to the transaction industry in the previous month. The interaction term tests whether the effect of previous-month industry share differs for purchases relative to sales. The marginal effect of industry share for purchases is calculated as the sum of previous-month industry share and the interaction between previous-month industry share and the purchase dummy. Log total previous-month manager holdings is included to control for the overall size of the manager's portfolio. Standard errors are clustered at the manager level and reported in parentheses. The regressions include manager fixed effects and industry-month fixed effects. Coefficients are measured in decimal values. The stars indicate statistical significance: * 10%, ** 5%, *** 1%.

Table 9: Holdings-based risk interaction fixed-effects regression of abnormal returns

Panel A: High-spread loans

	Baseline f2	Baseline f3
Previous-month industry share	-0.0076	-0.0088
	(0.0096)	(0.0124)
High-spread loan	0.0010	0.0018*
	(0.0007)	(0.0009)
Previous-month industry share × High-spread loan	0.0006	-0.0058
	(0.0051)	(0.0094)
Log total previous-month manager holdings	0.0006**	0.0009**
	(0.0003)	(0.0004)
General manager experience	-0.0018***	-0.0023***
	(0.0005)	(0.0006)
Transaction price	-0.0001	-0.0001
	(0.0002)	(0.0002)
Log transaction volume	0.0001	0.0002
	(0.0002)	(0.0002)
Average spread	-0.0005	-0.0007
	(0.0004)	(0.0005)
Rating score	-0.0004*	-0.0002
	(0.0002)	(0.0002)
Purchase dummy	0.0020***	0.0013***
	(0.0004)	(0.0004)
Constant	0.0144	0.0078
	(0.0192)	(0.0215)
Marginal effect of industry share in high-spread loans	-0.0069	-0.0146
	(0.0094)	(0.0118)
Observations	443,900	439,573

	Baseline f2	Baseline f3
R-squared	0.0879	0.0880

Panel B: Low-rated loans

	Baseline f2	Baseline f3
Previous-month industry share	-0.0019	-0.0076
	(0.0103)	(0.0114)
Low-rated loan	0.0012	0.0001
	(0.0009)	(0.0011)
Previous-month industry share × Low-rated loan	-0.0122	-0.0100
	(0.0084)	(0.0102)
Log total previous-month manager holdings	0.0006**	0.0009**
	(0.0003)	(0.0004)
General manager experience	-0.0018***	-0.0023***
	(0.0005)	(0.0006)
Transaction price	-0.0001	-0.0001
	(0.0002)	(0.0002)
Log transaction volume	0.0001	0.0002
	(0.0002)	(0.0002)
Average spread	-0.0002	-0.0003
	(0.0003)	(0.0004)
Rating score	-0.0004	0.0001
	(0.0003)	(0.0004)
Purchase dummy	0.0020***	0.0013***
	(0.0004)	(0.0004)
Constant	0.0135	0.0039
	(0.0198)	(0.0222)
Marginal effect of industry share in low-rated loans	-0.0142	-0.0176
	(0.0098)	(0.0132)

	Baseline f2	Baseline f3
Observations	443,900	439,573
R-squared	0.0878	0.0879

Notes: This table reports estimates from fixed-effects regressions of winsorised abnormal returns on previous-month industry share, loan-risk indicators, and their interaction terms. Panel A tests whether the effect of previous-month industry share differs for high-spread loans. Panel B tests whether the effect differs for low-rated loans. The dependent variables are abret_f2_w and abret_f3_w, representing the two forward abnormal return horizons. Abnormal returns are measured from the manager's perspective: purchase returns are left unchanged, while sale returns are multiplied by -1 before winsorization. Previous-month industry share is measured as the share of the manager's holdings allocated to the transaction industry in the previous month. High-spread loans are defined as loans with an average spread above the sample median. Low-rated loans are defined as loans with a rating score strictly above the sample median. The marginal effect of industry share in risky loans is calculated as the sum of previous-month industry share and the relevant interaction term. Log total previous-month manager holdings is included to control for the overall size of the manager's portfolio. Standard errors are clustered at the manager level and reported in parentheses. The regressions include manager fixed effects and industry-month fixed effects. Coefficients are measured in decimal values. The stars indicate statistical significance: * 10%, ** 5%, *** 1%.

Table 10: Holdings-based fixed-effects regressions of actual downside risk

Panel A: Probability of negative actual returns

	Negative return f2	**Negative return f3**
Previous-month industry share	0.0449	0.1360
	(0.0996)	(0.1066)
Log total previous-month manager holdings	0.0089	0.0074
	(0.0062)	(0.0060)
General manager experience	0.0064	0.0057
	(0.0071)	(0.0065)
Transaction price	0.0030***	0.0026***
	(0.0008)	(0.0009)
Log transaction volume	0.0068***	0.0059***
	(0.0017)	(0.0018)
Average spread	-0.0006	-0.0004
	(0.0028)	(0.0029)
Rating score	0.0007	-0.0022
	(0.0020)	(0.0028)
Purchase dummy	-0.5291***	-0.5757***
	(0.0082)	(0.0082)
Constant	0.0855	0.2333
	(0.1516)	(0.1746)
Observations	646,392	637,965
R-squared	0.3502	0.3999

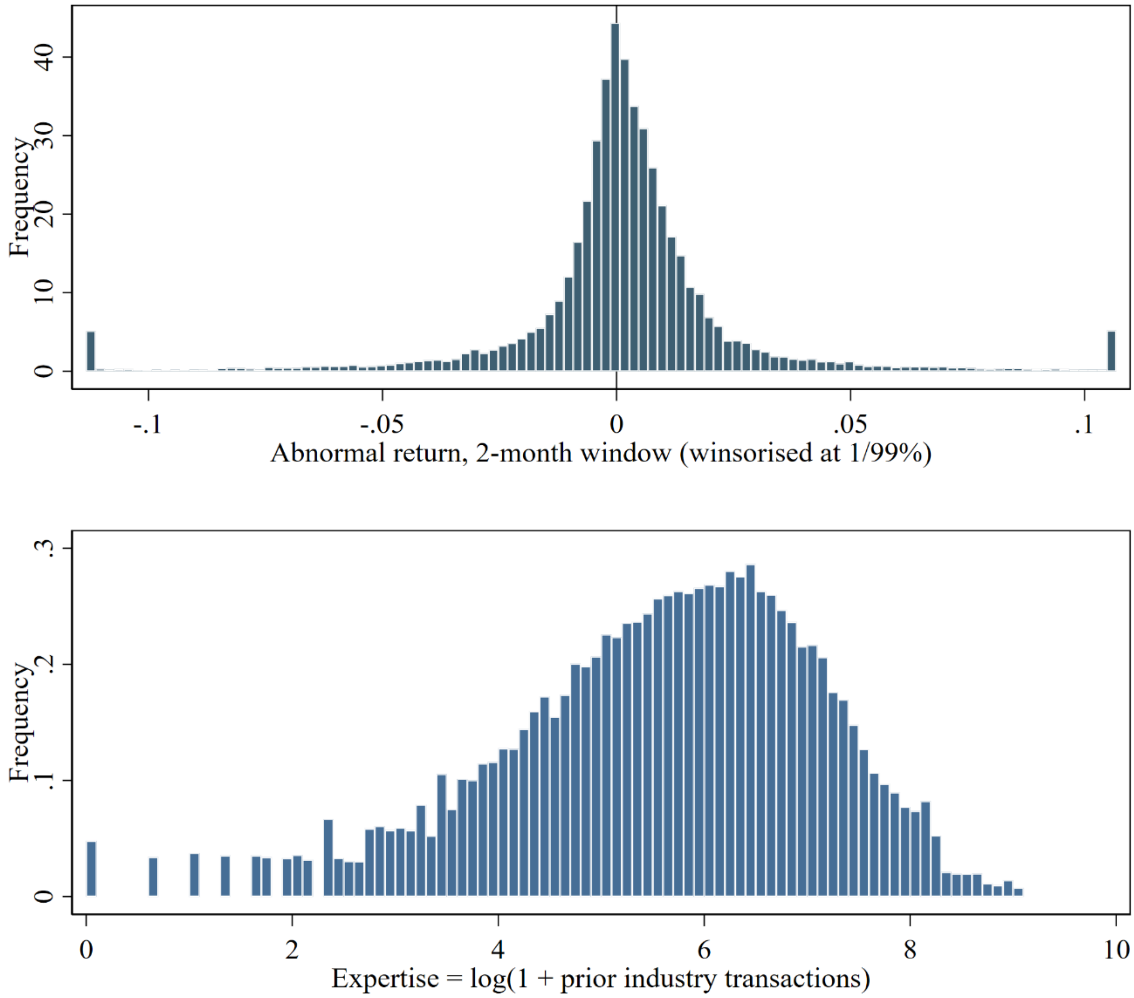
Panel B: Actual loss severity

	Loss severity f2	**Loss severity f3**
Previous-month industry share	-0.0095	-0.0152
	(0.0098)	(0.0121)
Log total previous-month manager holdings	-0.0003	-0.0004

	Loss severity f2	Loss severity f3
	(0.0003)	(0.0004)
General manager experience	0.0007	0.0009*
	(0.0005)	(0.0005)
Transaction price	-0.0018***	-0.0023***
	(0.0001)	(0.0001)
Log transaction volume	0.0001	0.0002
	(0.0002)	(0.0002)
Average spread	0.0007***	0.0011***
	(0.0003)	(0.0003)
Rating score	0.0007***	0.0009***
	(0.0002)	(0.0002)
Purchase dummy	-0.0055***	-0.0094***
	(0.0006)	(0.0008)
Constant	0.1718***	0.2277***
	(0.0113)	(0.0128)
Observations	646,392	637,965
R-squared	0.3746	0.3952

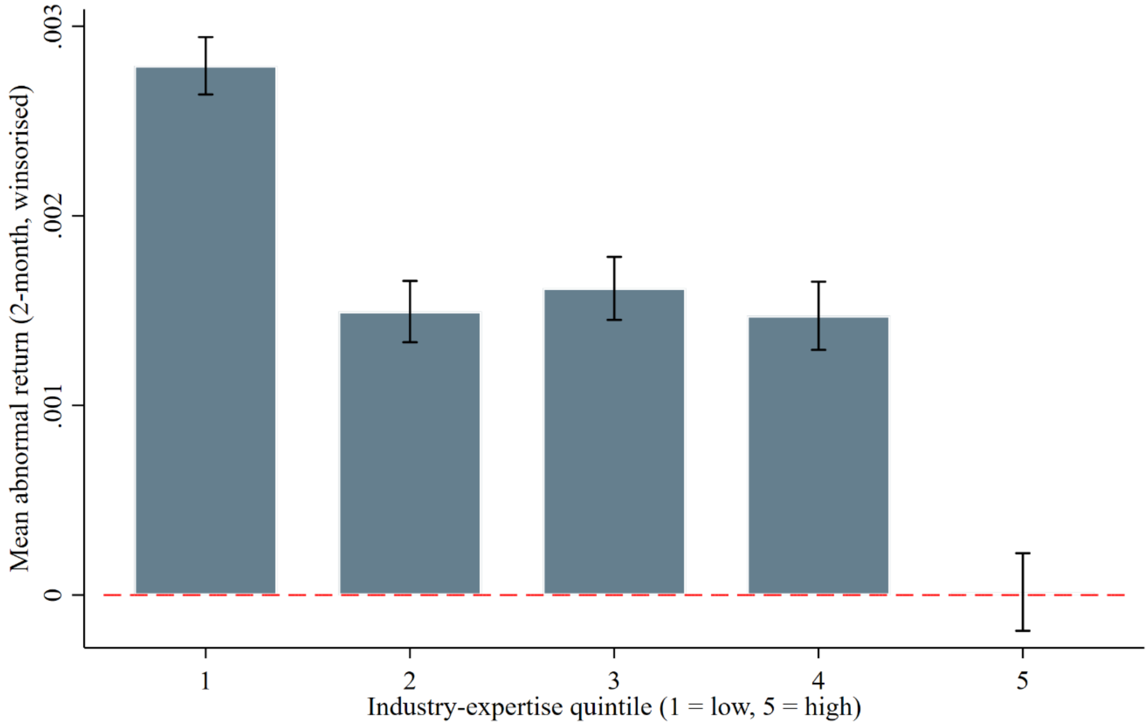
Notes: This table reports estimates from fixed-effects regressions of actual downside risk on previous-month industry share and transaction-level controls. Panel A uses negative actual return indicators as dependent variables, equal to one when the winsorised forward actual return is below zero and zero otherwise. Panel B uses actual loss severity as the dependent variable, defined as the absolute value of the negative actual return and zero otherwise. Actual returns are measured from the manager's perspective: purchase returns are left unchanged, while sale returns are multiplied by -1 before winsorization. Previous-month industry share is measured as the share of the manager's holdings allocated to the transaction industry in the previous month. Log total previous-month manager holdings is included to control for the overall size of the manager's portfolio. Standard errors are clustered at the manager level and reported in parentheses. The regressions include manager fixed effects and industry-month fixed effects. Coefficients are measured in decimal values. The stars indicate statistical significance: * 10%, ** 5%, *** 1%.

Figure 1: Distribution of abnormal returns and the expertise measure



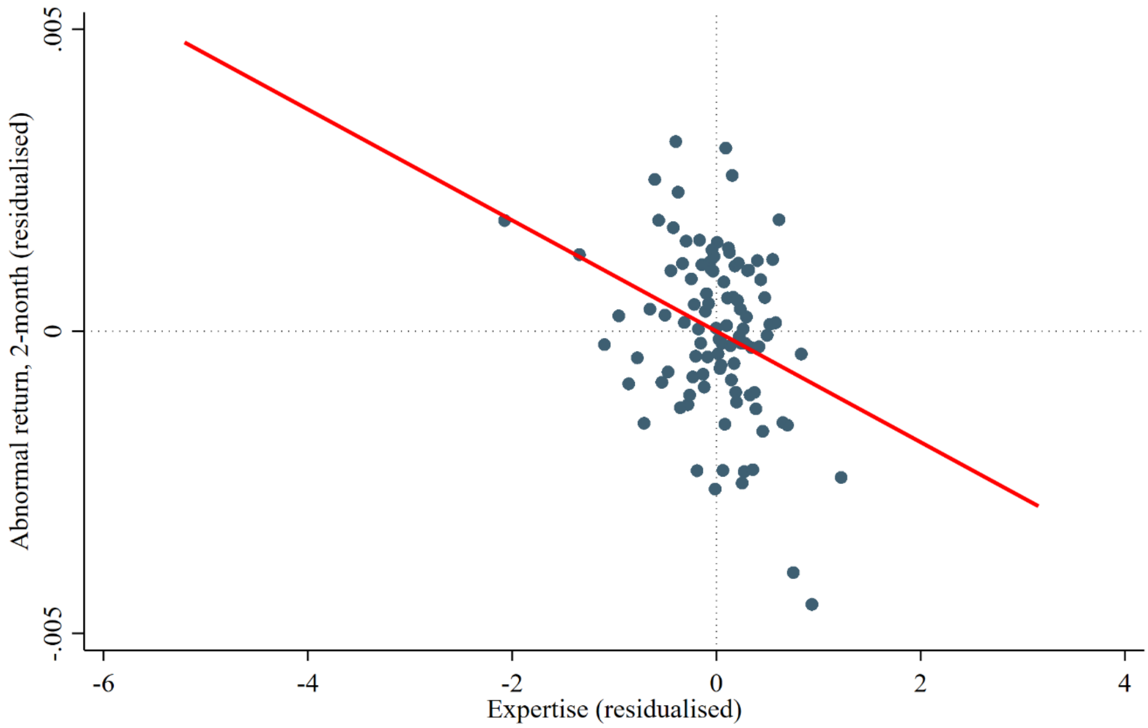
Notes: Top panel: distribution of two-month abnormal returns (winsorised at the 1%/99% tails). Bottom panel: distribution of the expertise measure log(1 + prior industry transactions). The expertise measure captures the cumulative number of transactions a manager has executed in the same Moody's industry prior to the current transaction.

Figure 2: Abnormal returns by industry-expertise quintile



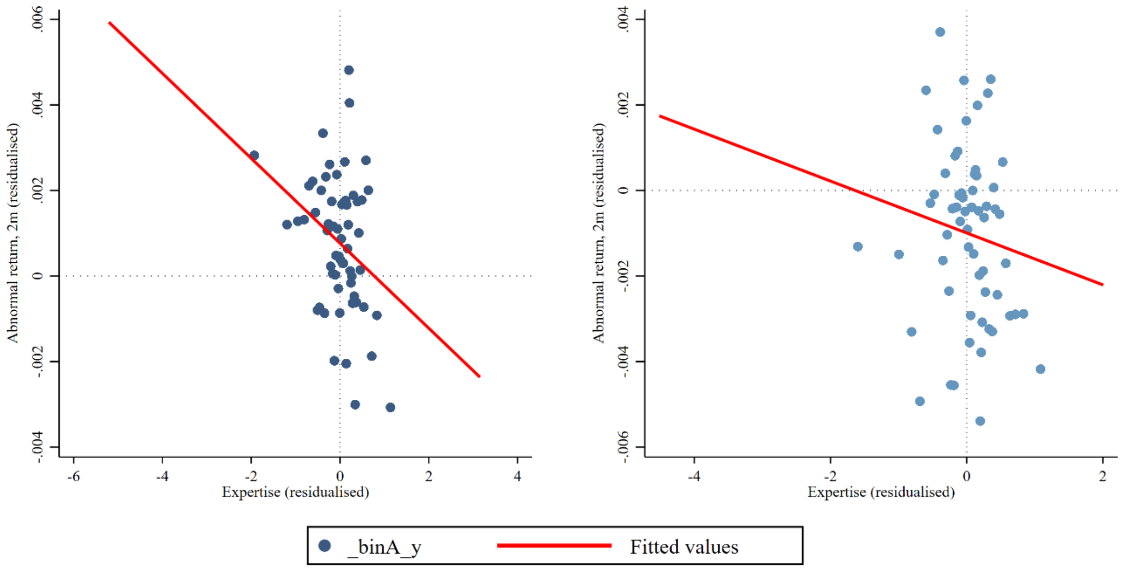
Notes: Within-month quintiles of the expertise measure. Bars show the unconditional mean two-month abnormal return per quintile. Error bars show 95% confidence intervals based on standard errors of the mean. Abnormal returns are winsorised at the 1%/99% tails and measured from the manager's perspective.

Figure 3: Abnormal returns and industry expertise (binscatter)



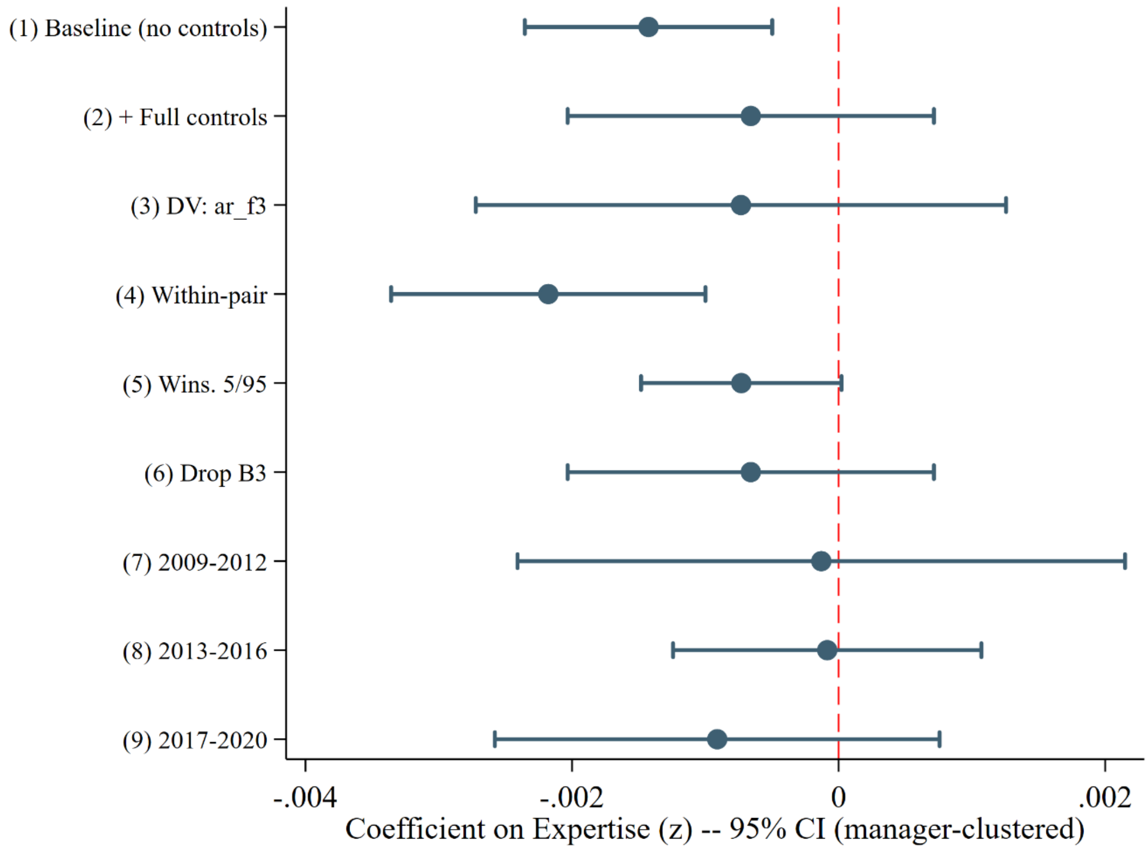
Notes: Each point is the average of one of 100 equal-sized bins on residualised expertise. Both axes are residualised against manager fixed effects and industry-month fixed effects. The red line shows the OLS fit through the binned data. Abnormal returns are winsorised at the 1%/99% tails.

Figure 4: Industry expertise and abnormal returns by transaction direction



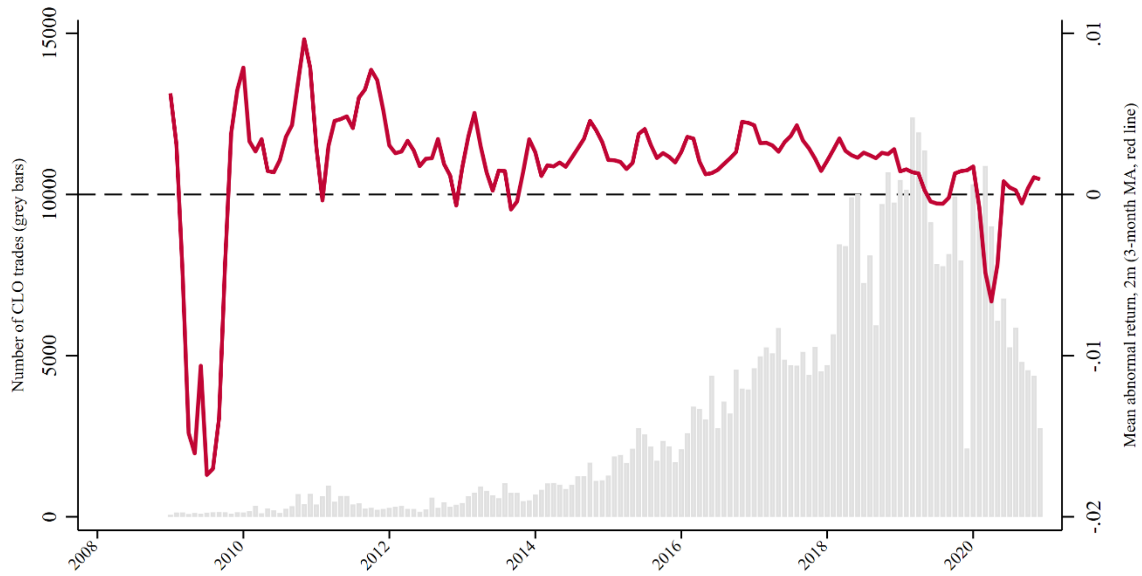
Notes: Sixty-bin binscatters of residualised two-month abnormal returns against residualised expertise, estimated separately for purchases (Panel A) and sales (Panel B). Residualisation as in Figure 3. The red line shows the OLS fit through the binned data.

Figure 5: Expertise coefficient on abnormal returns across specifications



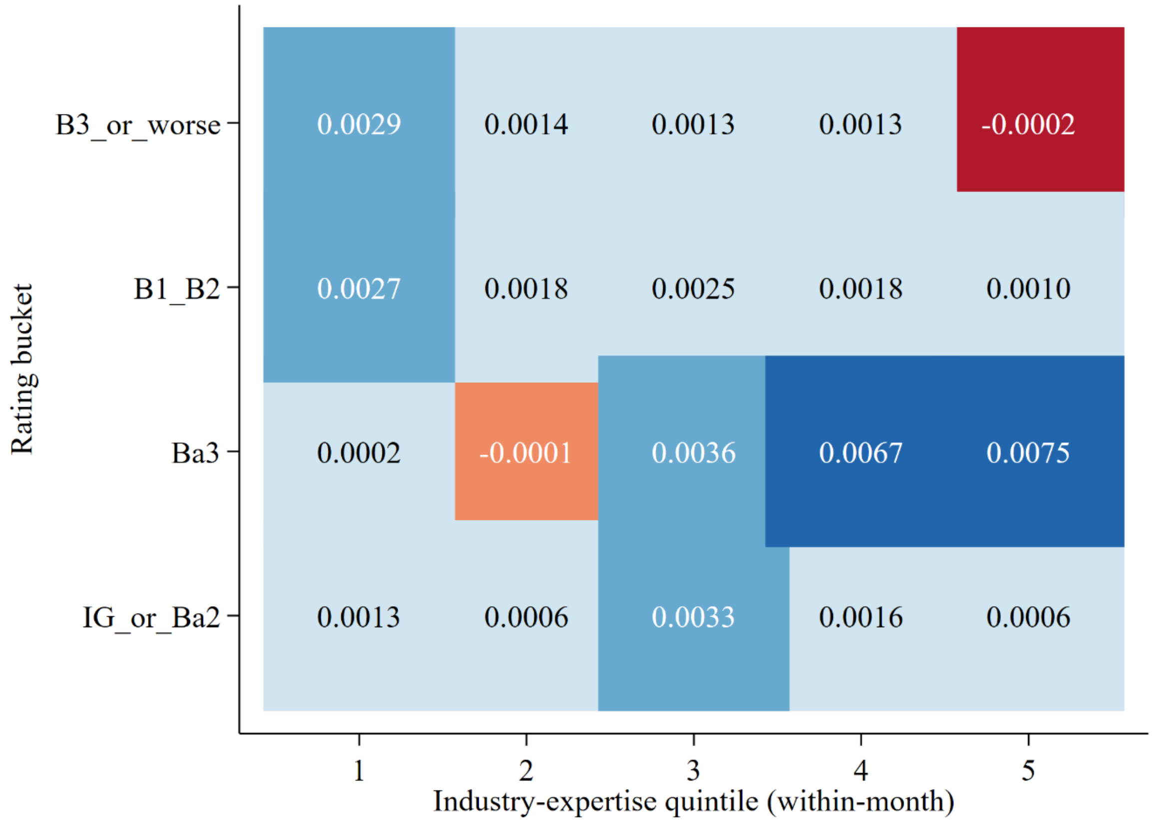
Notes: Each row reports the standardised expertise coefficient and its 95% confidence interval from a different specification or sample of the H1 regression. The expertise variable is standardised to a z-score within each sample. Standard errors are clustered at the manager level. The red dashed line marks zero.

Figure 6: Time-series of CLO trading activities and abnormal returns



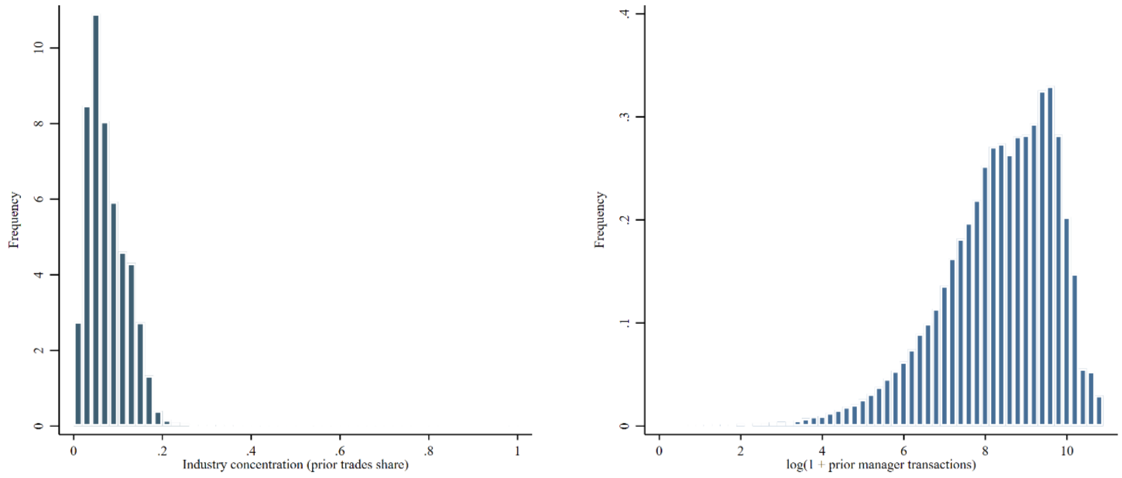
Notes: Grey bars show the number of CLO loan transactions per calendar month (right axis). The red line shows the equal-weighted mean two-month abnormal return, smoothed as a three-month moving average (left axis). Abnormal returns are winsorised at the 1%/99% tails and measured from the manager's perspective.

Figure 7: Mean abnormal returns by rating bucket and expertise quintile



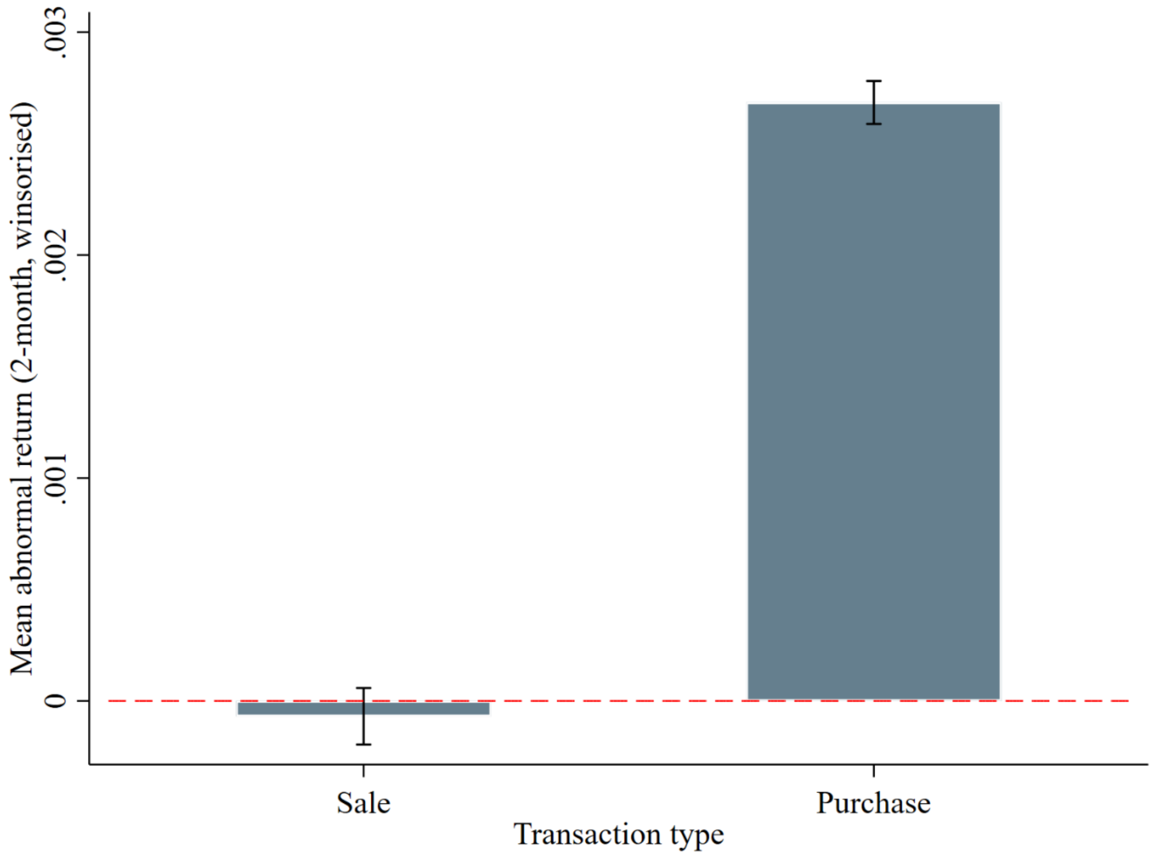
Notes: Cells show the mean two-month abnormal return for each rating-bucket and within-month expertise-quintile combination. Rating buckets are defined on the Moody's numeric scale: IG_or_Ba2 (investment grade to Ba2), Ba3, B1_B2, and B3_or_worse. Colour shading is proportional to the cell value on a diverging red–blue scale.

Figure 8: Distributions of concentration and experience measures



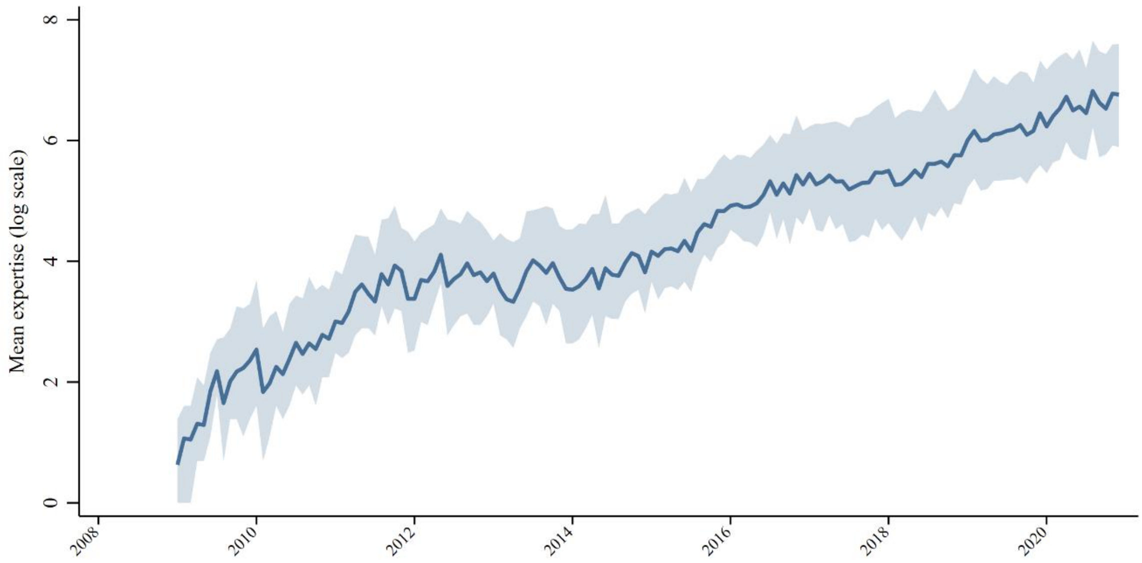
Notes: Left panel: distribution of industry concentration, measured as the share of a manager's prior transactions allocated to the current transaction industry. Right panel: distribution of general manager experience, measured as log(1 + total prior transactions by the same manager across all industries).

Figure 9: Mean abnormal returns by transaction type



Notes: Bars show the unconditional mean two-month abnormal return separately for sales and purchases. Error bars show 95% confidence intervals based on standard errors of the mean. Abnormal returns are winsorised at the 1%/99% tails and measured from the manager's perspective: purchase returns are left unchanged, while sale returns are multiplied by -1.

Figure 10: Mean industry expertise over time



Notes: The line shows the cross-sectional mean of the expertise measure log(1 + prior industry transactions) per calendar month. The shaded band shows the interquartile range. The upward trend reflects the mechanical accumulation of transaction history over the sample period.