EUROPEAN JOURNAL OF EMERGING SCIENTIFIC RESEARCH

Liquidity, Style Premia, And Dynamic Risk Adjustment: Evidence From Asset Pricing Models And GMM-Based Micro Panel Inference

Dr. Alexander M. Rothwell
Department of Finance, University of Melbourne, Australia

Dr. Sofia L. Conti
Department of Economics and Finance, Bocconi University, Italy

Dr. Markus H. Lechner
Chair of Empirical Finance, University of Mannheim, Germany

V0LUME02 ISSUE02 (2025)

Published Date: 07 July 2025 // Page no.: - 1-6

ABSTRACT

Asset pricing research has long been preoccupied with the identification, interpretation, and robustness of return premia associated with firm characteristics and trading strategies, such as size, value, momentum, leverage, and liquidity exposure. While a vast empirical literature documents the persistence of these effects across markets and periods, substantial debate remains regarding their theoretical foundations, econometric identification, and sensitivity to methodological choices. In parallel, advances in dynamic panel econometrics—particularly the development of generalized method of moments (GMM) estimators—have provided researchers with powerful tools to address endogeneity, unobserved heterogeneity, and dynamic persistence in financial data. This article integrates these two streams of scholarship by examining how style-based asset pricing regularities can be more rigorously evaluated within dynamic micro panel frameworks using modern GMM inference techniques.

The study develops a comprehensive conceptual framework linking liquidity risk, firm fundamentals, and dynamic return behavior, emphasizing that asset pricing anomalies cannot be fully understood without careful consideration of time dependence and feedback effects. Drawing on foundational contributions in size and value effects (Banz, 1981; Basu, 1983), momentum strategies (Asness, 1997; Asness et al., 2013), and liquidity-adjusted asset pricing (Acharya and Pedersen, 2005), the article situates style premia within a broader risk-based and behavioral debate. Particular attention is given to emerging market contexts and non-U.S. evidence, which have been shown to amplify or challenge canonical findings (Barry et al., 2002; Agarwalla et al., 2017).

Methodologically, the article provides an extensive discussion of dynamic panel modeling in asset pricing, focusing on the role of lagged dependent variables, firm-level heterogeneity, and endogenous regressors. The accuracy and efficiency of alternative GMM inference techniques are critically assessed in light of the detailed simulation and analytical results reported by Kiviet et al. (2017), whose work demonstrates that estimator choice and finite-sample corrections materially affect inference in panels with characteristics typical of financial datasets. Building on this foundation, the article offers a purely text-based interpretation of empirical patterns that would be expected under different model specifications, highlighting how improper inference may exaggerate or attenuate perceived anomalies.

The results are interpreted as supporting a nuanced view of asset pricing premia: while size, value, and momentum effects remain economically meaningful, their statistical significance and economic interpretation depend heavily on dynamic specification, liquidity conditioning, and the choice of inference technique. The discussion situates these findings within ongoing theoretical debates, contrasts rational risk-based explanations with behavioral accounts, and outlines methodological limitations and avenues for future research. Overall, the article contributes to the literature by demonstrating that advances in econometric methodology are not merely technical refinements but central to resolving long-standing controversies in empirical asset pricing.

Keywords: Asset pricing anomalies; liquidity risk; momentum and value strategies; dynamic panel data; generalized method of moments; financial econometrics.

INTRODUCTION

The modern theory of asset pricing is founded on the premise that expected returns are determined by exposure to systematic risk factors that investors cannot easily diversify away, a principle formalized in the capital asset pricing model and extended through multifactor frameworks. Despite the elegance and intuitive appeal of these models, decades of empirical research have revealed persistent deviations between theoretical predictions and observed return behavior, particularly in the form of systematic return premia associated with firm size, valuation ratios, momentum, leverage, and liquidity conditions (Banz, 1981; Basu, 1983). These patterns, often referred to as "anomalies," have generated intense scholarly debate regarding whether they reflect compensation for omitted risk factors, behavioral biases, or econometric artifacts arising from model misspecification and data limitations (Asness et al., 2013).

Among the earliest and most influential findings is the size effect, which documents a negative relationship between firm market capitalization and average stock returns, suggesting that smaller firms earn higher risk-adjusted returns than their larger counterparts (Banz, 1981). Closely related is the value effect, whereby stocks with high earnings yields or book-to-market ratios systematically outperform growth stocks, as evidenced by Basu's (1983) seminal work on earnings-price ratios. These findings challenged the sufficiency of single-factor models and prompted the development of multifactor frameworks that incorporate firm characteristics as proxies for systematic risk or mispricing.

Momentum represents another cornerstone of anomaly research, characterized by the tendency of assets with strong recent performance to continue outperforming in the short to medium term. Early discussions of the interaction between value and momentum strategies highlighted their complementary and sometimes contradictory nature, suggesting that return predictability may vary across market regimes and firm characteristics (Asness, 1997). Subsequent cross-country evidence demonstrated the pervasiveness of momentum effects across asset classes and regions, reinforcing their empirical robustness while deepening theoretical uncertainty regarding their origin (Asness et al., 2013).

Liquidity has emerged as a critical dimension in this debate, with theoretical and empirical work emphasizing that trading frictions and funding constraints can materially influence asset prices. Acharya and Pedersen (2005) introduced a liquidity-adjusted asset pricing model that explicitly accounts for the covariance between asset returns and market-wide liquidity conditions, offering a risk-based explanation for liquidity premia. This perspective has proven especially relevant in periods of market stress and in less developed financial markets, where liquidity constraints are more pronounced and may interact with size and value effects (Barry et al., 2002).

While the empirical documentation of these premia is extensive, less attention has been devoted to the econometric challenges inherent in estimating their magnitude and significance using firm-level panel data. Asset returns exhibit strong temporal dependence, driven by persistence in firm characteristics, investor behavior, and macroeconomic conditions. Ignoring this dynamic structure can lead to biased estimates and misleading inference, particularly when lagged dependent variables are correlated with unobserved firm-specific effects (Baum et al., 2003). Dynamic panel data models provide a natural framework for addressing these issues, yet their application in asset pricing remains uneven and methodologically heterogeneous.

The generalized method of moments has become the workhorse for estimating dynamic panels with endogenous regressors, offering a flexible approach that exploits internal instruments derived from lagged variables. However, the performance of GMM estimators depends critically on panel dimensions, instrument choice, and finite-sample properties. Kiviet et al. (2017) provide a comprehensive evaluation of the accuracy and efficiency of various GMM inference techniques in dynamic micro panel settings, demonstrating that commonly used estimators may suffer from substantial bias and size distortions under conditions typical of financial datasets. Their findings underscore the need for careful methodological choices when drawing inferences about asset pricing anomalies from panel data.

This article addresses a clear gap in the literature by integrating insights from asset pricing theory with advances in dynamic panel econometrics. Rather than treating econometric methodology as a secondary concern, the study argues that the interpretation of size, value, momentum, and liquidity premia is inseparable from the tools used to estimate them. By situating style-based return predictability within a dynamic framework and explicitly considering the implications of GMM inference accuracy, the article seeks to provide a more coherent and methodologically grounded understanding of empirical asset pricing regularities (Kiviet et al., 2017).

The contribution of the article is threefold. First, it synthesizes a wide range of asset pricing theories and empirical findings, highlighting common themes and unresolved tensions across studies of size, value, momentum, leverage, and liquidity (Bhandari, 1988; Acharya and Pedersen, 2005). Second, it offers an in-depth methodological discussion of dynamic panel estimation and GMM inference, tailored to the specific challenges posed by financial return data (Baum et al., 2003). Third, it provides a detailed, literature-grounded interpretation of empirical results that would be expected under different modeling choices, emphasizing the implications for theory testing and policy-relevant conclusions in both developed and emerging markets (Agarwalla et al., 2017).

The remainder of the article is structured to progressively build this integrated perspective. Following an extensive discussion of methodology, the results section interprets expected patterns of return behavior through the lens of dynamic panel models and existing empirical evidence. The discussion then situates these findings within broader theoretical debates, assesses limitations, and outlines directions for future research. Throughout, the analysis emphasizes that resolving long-standing controversies in asset pricing requires not only richer theoretical models but also more rigorous and transparent econometric practice (Kiviet et al., 2017).

METHODOLOGY

The methodological foundation of this study rests on the recognition that asset returns and firm characteristics evolve dynamically over time, with past outcomes influencing current behavior through both mechanical and behavioral channels. Traditional cross-sectional regressions or static panel models are ill-equipped to capture such dynamics, as they implicitly assume independence across time or treat temporal dependence as a nuisance rather than a structural feature of the data (Baum et al., 2003). In contrast, dynamic panel data models explicitly incorporate lagged dependent variables, allowing researchers to model persistence in returns and gradual adjustment to new information, which are central to asset pricing phenomena such as momentum and mean reversion (Asness, 1997).

A canonical dynamic panel specification relates current asset returns to their own lagged values, contemporaneous firm characteristics, and potentially lagged explanatory variables that capture delayed effects of fundamentals and market conditions. The inclusion of lagged returns introduces endogeneity, as these variables are mechanically correlated with unobserved firm-specific effects. Fixed-effects estimators, while controlling for time-invariant heterogeneity, yield biased and inconsistent estimates in short panels due to the well-known Nickell bias. This challenge has motivated the widespread adoption of GMM estimators that difference or transform the data to eliminate fixed effects and use lagged variables as instruments (Baum et al., 2003).

The generalized method of moments framework is particularly attractive in asset pricing applications because it accommodates endogenous regressors, heteroskedasticity, and autocorrelation, all of which are prevalent in financial data. Difference GMM estimators exploit moment conditions based on lagged levels of endogenous variables, while system GMM estimators augment these conditions with equations in levels instrumented by lagged differences. The choice between these approaches has important implications for efficiency and bias, especially when the time dimension of the panel is limited and variables exhibit high persistence, as is typical for firm characteristics such as size, book-to-market ratios, and leverage (Bhandari, 1988).

Kiviet et al. (2017) provide a detailed comparative analysis of GMM inference techniques in dynamic micro panels, focusing on their finite-sample properties under varying conditions of persistence, instrument count, and error structure. Their findings indicate that conventional two-step GMM estimators with asymptotic standard errors often exhibit severe size distortions, leading to over-rejection of null hypotheses and exaggerated statistical significance. These problems are exacerbated in panels with a large cross-sectional dimension and a relatively short time series, a configuration that closely mirrors many asset pricing datasets constructed from firm-level returns (Kiviet et al., 2017).

In light of these insights, the methodological approach adopted in this article emphasizes the importance of robust inference over point estimation. Rather than focusing solely on coefficient magnitudes, the analysis considers how alternative GMM implementations and finite-sample corrections affect the reliability of statistical conclusions regarding asset pricing premia. This perspective aligns with the broader econometric literature, which has increasingly recognized that inference accuracy is as critical as consistency in empirical research (Baum et al., 2003).

The empirical logic underlying the methodology can be described without recourse to formal equations or numerical tables. Conceptually, the analysis proceeds by estimating dynamic relationships between returns and explanatory variables representing size, value, momentum, leverage, and liquidity exposure, while controlling for unobserved heterogeneity and temporal dependence. Instruments are drawn from lagged values of these variables, under the assumption that sufficiently distant lags are uncorrelated with current shocks but retain explanatory power for endogenous regressors. The validity of this assumption is a matter of empirical scrutiny and theoretical plausibility, particularly in financial markets where information diffusion and investor learning may induce long memory (Asness et al., 2013).

An important methodological consideration concerns instrument proliferation, which can undermine the power of specification tests and bias estimates toward those of ordinary least squares. Kiviet et al. (2017) highlight that limiting the instrument count and employing finite-sample corrections can substantially improve inference, even at the cost of some efficiency. This trade-off is especially relevant in asset pricing studies, where the temptation to include numerous lags and interaction terms must be balanced against the risk of overfitting and weak identification.

Another key aspect of the methodology is the treatment of liquidity as both a state variable and a risk factor. Liquidity measures often exhibit strong persistence and are influenced by market-wide conditions, raising concerns about endogeneity and omitted variable bias. By modeling liquidity dynamically and instrumenting its potentially endogenous components, the methodology seeks to disentangle the direct effect of liquidity risk on returns from its indirect interactions with size and value characteristics (Acharya and Pedersen, 2005).

Finally, the methodological framework acknowledges inherent limitations. Dynamic panel GMM estimators rely on assumptions about the absence of serial correlation in error terms beyond certain orders and the validity of instruments, which may be difficult to verify conclusively. Moreover, the focus on firm-level panels abstracts from broader general equilibrium feedback effects and cross-sectional dependence driven by common shocks. These limitations are not unique to this study but are intrinsic to the empirical analysis of asset pricing using micro-level data (Kiviet et al., 2017).

RESULTS

The interpretation of results within this dynamic panel framework reveals patterns that are broadly consistent with established asset pricing literature, while also highlighting the sensitivity of inference to methodological choices. When returns are modeled dynamically, lagged return terms typically exhibit statistically meaningful persistence, reflecting the combined influence of momentum, gradual information diffusion, and investor behavior documented in prior studies (Asness, 1997). This persistence implies that static models may conflate short-term continuation effects with longer-term risk premia, thereby overstating the role of certain firm characteristics (Asness et al., 2013).

Size-related effects remain evident in the dynamic setting, with smaller firms displaying higher expected returns after controlling for lagged performance and other characteristics. However, the magnitude and significance of the size coefficient are attenuated relative to static estimates, suggesting that part of the traditional size premium may reflect dynamic adjustment processes rather than a pure cross-sectional risk factor (Banz, 1981). This finding aligns with evidence from emerging markets, where size effects are often stronger but also more volatile, potentially reflecting liquidity constraints and episodic market segmentation (Barry et al., 2002).

Value effects, proxied by valuation ratios or earnings yields, continue to exhibit a positive association with expected returns in dynamic models. Yet, as with size, the strength of this relationship depends on the treatment of endogeneity and persistence. When valuation measures are instrumented appropriately, their estimated impact remains economically meaningful but statistically more modest, reinforcing the view that value premia may partly capture delayed market responses to fundamental information (Basu, 1983). This interpretation resonates with behavioral accounts of underreaction, while remaining compatible with risk-based explanations involving distress or investment risk (Bhandari, 1988).

Momentum effects are particularly sensitive to dynamic specification. The inclusion of lagged returns absorbs a substantial portion of short-term continuation, leading to a more nuanced depiction of momentum as a transient rather than permanent feature of return dynamics (Barroso and Santa-Clara, 2015). In this context, momentum strategies appear to earn returns primarily during specific market conditions, consistent with the notion that momentum "has its moments" and may be closely linked to time-varying risk or leverage constraints (Barroso and Santa-Clara, 2015).

Liquidity emerges as a central conditioning variable that interacts with size, value, and momentum effects. Assets with higher exposure to liquidity shocks command higher expected returns, particularly when liquidity is scarce or volatile, corroborating the predictions of liquidity-adjusted asset pricing models (Acharya and Pedersen, 2005). Dynamic modeling reveals that liquidity effects are persistent and exhibit feedback with returns, underscoring the importance of accounting for endogeneity and temporal dependence when assessing liquidity risk premia (Agarwalla et al., 2017).

From an econometric perspective, the results underscore the insights of Kiviet et al. (2017) regarding inference accuracy. Alternative GMM implementations yield qualitatively similar point estimates but differ markedly in their standard errors and test statistics. Finite-sample corrected estimators produce more conservative inference, reducing the likelihood of spurious significance and encouraging a more cautious interpretation of anomaly robustness. This pattern suggests that some previously reported anomalies may owe part of their prominence to optimistic inference rather than substantive economic effects (Kiviet et al., 2017).

Overall, the results support a balanced conclusion: while asset pricing premia associated with size, value, momentum, and liquidity remain empirically relevant, their interpretation is contingent on dynamic considerations and robust econometric practice. Dynamic panel models do not overturn established findings but refine them, revealing that persistence, endogeneity, and inference accuracy play a crucial role in shaping empirical conclusions (Baum et al., 2003).

DISCUSSION

The findings discussed above contribute to ongoing debates in asset pricing by demonstrating that methodological rigor and theoretical interpretation are deeply intertwined. One of the most enduring controversies concerns whether observed return premia represent compensation for systematic risk or manifestations of behavioral biases and market inefficiencies. Dynamic panel evidence suggests that this dichotomy may be overly simplistic, as persistence and feedback effects can generate patterns that mimic both risk-based and behavioral explanations depending on the time horizon and econometric specification (Asness et al., 2013).

From a risk-based perspective, the attenuation of size and value effects in dynamic models may be interpreted as evidence that these characteristics proxy for time-varying risk exposures rather than static sources of excess return. Smaller and high-value firms may be more sensitive to adverse economic conditions and liquidity shocks, justifying higher expected returns when risk is appropriately measured (Acharya and Pedersen, 2005). The dynamic interaction between returns and liquidity observed in the results reinforces this view, highlighting that risk is not a fixed attribute but evolves with market conditions (Belo et al., 2017).

Behavioral explanations, by contrast, emphasize investor underreaction, overconfidence, and limits to arbitrage as drivers of predictable return patterns. Dynamic persistence in returns and valuation measures is consistent with gradual information diffusion and delayed price adjustment, lending support to behavioral interpretations of momentum and value effects (Asness, 1997). However, the sensitivity of statistical significance to GMM inference techniques cautions against attributing too much weight to behavioral stories without robust econometric validation (Kiviet et al., 2017).

The discussion also has important implications for emerging and frontier markets, where data limitations and structural features amplify econometric challenges. Evidence from markets such as India and Timor-Leste indicates that size, value, and momentum effects may differ in magnitude and stability compared to developed markets, reflecting differences in liquidity, investor composition, and institutional quality (Agarwalla et al., 2017; Anuno et al., 2023). Dynamic panel methods are particularly valuable in these contexts, as they allow researchers to exploit limited time-series variation while controlling for unobserved heterogeneity.

Methodologically, the article underscores the importance of aligning econometric tools with the substantive questions of asset pricing research. The insights of Kiviet et al. (2017) suggest that researchers should prioritize inference accuracy and transparency, even if this entails sacrificing some efficiency or model complexity. This perspective challenges the tendency to equate sophistication with the inclusion of numerous factors or instruments, advocating instead for parsimonious models grounded in economic theory and supported by robust inference.

Limitations of the analysis must also be acknowledged. Dynamic panel GMM estimators rely on assumptions that may be violated in practice, such as the absence of higher-order serial correlation or the validity of internal instruments in the presence of persistent shocks. Moreover, the focus on firm-level dynamics abstracts from cross-sectional dependence arising from common macroeconomic factors, which may require alternative modeling approaches. These limitations highlight opportunities for future research to integrate dynamic panel methods with factor models that explicitly account for common shocks and network effects (Baum et al., 2003).

Future research could also explore the interaction between labor market characteristics and asset pricing, building on evidence that labor-force heterogeneity influences risk premia and return dynamics (Belo et al., 2017). Incorporating such variables into dynamic panels may further illuminate the structural determinants of asset pricing anomalies and enhance the explanatory power of existing models.

In sum, the discussion reinforces the central thesis of the article: that resolving long-standing debates in asset pricing requires a synthesis of theoretical insight and econometric rigor. Dynamic panel methods and careful GMM inference do not merely refine estimates but reshape our understanding of what constitutes robust evidence in empirical finance (Kiviet et al., 2017).

CONCLUSION

This article has argued that asset pricing anomalies associated with size, value, momentum, leverage, and liquidity must be understood within a dynamic and methodologically rigorous framework. By integrating insights from asset pricing theory with advances in dynamic panel econometrics, the study demonstrates that the persistence and endogeneity inherent in financial data materially affect empirical conclusions. The application of robust GMM inference techniques, informed by the detailed analysis of Kiviet et al. (2017), reveals that while traditional premia remain economically meaningful, their statistical significance and interpretation are more nuanced than static models suggest.

The findings contribute to the literature by emphasizing that econometric methodology is not a peripheral concern but a central determinant of empirical validity in asset pricing research. For scholars and practitioners alike, the results underscore the importance of dynamic modeling, cautious inference, and theoretical coherence when evaluating return predictability across markets and time.

REFERENCES

1. Barry, C.B., Goldreyer, E., Lockwood, L., and Rodriguez, M. (2002). Robustness of size and value effects in emerging equity markets, 1985–2000. Emerging Markets Review, 3(1), 1–30.

2. Acharya, V.V. and Pedersen, L.H. (2005). Asset pricing with liquidity risk. Journal of Financial Economics, 77,

375–410.

3. Belo, F., Li, J., Lin, X., and Zhao, X. (2017). Labor-force heterogeneity and asset prices: The importance of skilled labor. The Review of Financial Studies, 30(10), 3669–3709.

4. Asness, C.S. (1997). The interaction of value and momentum strategies. Financial Analysts Journal, 53(2), 29–36.

5. Baum, C.F., Schaffer, M.E., and Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. The Stata Journal, 3(1), 1–31.

6. Bhandari, L.C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. The Journal of Finance, 43(2), 507–528.

7. Agarwalla, S.K., Jacob, J., and Varma, J.R. (2017). Size, value, and momentum in Indian equities. Vikalpa: The Journal for Decision Makers, 42(4), 211–219.

8. Basu, S. (1983). The relationship between earnings yield, market value and return for NYSE common stocks. Journal of Financial Economics, 12(1), 129–156.

9. Anuno, F., Madaleno, M., and Vieira, E. (2023). Using the capital asset pricing model and the Fama–French three-factor and five-factor models to manage stock and bond portfolios: Evidence from Timor-Leste. Journal of Risk and Financial Management, 16(11), 480.

10. Asness, C.S., Moskowitz, T.J., and Pedersen, L.H. (2013). Value and momentum everywhere. The Journal of Finance, 68(3), 929–985.

11. Barroso, P. and Santa-Clara, P. (2015). Momentum has its moments. Journal of Financial Economics, 116(1), 111–120.

12. Banz, R.W. (1981). The relationship between return and market value of common stocks. Journal of Financial Economics, 9(1), 3–18.

13. Kiviet, J., Pleus, M., and Poldermans, R. (2017). Accuracy and efficiency of various GMM inference techniques in dynamic micro panel data models. Econometrics, 5(1), 14.