Does Illiquidity Matter? An Errors-in-Variables Perspective

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ABSTRACT

Illiquidity is well known in the literature to be an important risk factor to consider in financial models of return. However, there is not much consensus on which measure should be used as a proxy for illiquidity. Our contributions mainly focus on the Pástor-Stambaugh measure in the context of the Fama-French three factor and more recently on the new five-factor model. In this survey article, we discuss our contributions on the subject in an errors-in-variables perspective. In particular, we propose new robust instruments that are developed and applied in different stages of our research. Robustness tests of these new instruments are performed in this research. Overall, our new instruments coupled with the GMM estimator show that either in a cross sectional, panel data, or recursive/rolling regression compared to the Kalman filter framework, that the most significant factor seems to be the market factor. This might be seen as in line with Cochrane's concern about a "zoo of factors".

Keywords: GMM, higher moments, Kalman filter, illiquidity, robust instruments, weak instrumental variables test.

¿Es importante la iliquidez? Un análisis desde el enfoque de errores en variables

RESUMEN

La iliquidez es bien conocida en la literatura como un importante factor de riesgo a considerar en los modelos financieros de retorno. Sin embargo, no hay mucho consenso sobre la medida que se debe utilizar como proxy para la iliquidez. Nuestras aportaciones a la cuestión se centran principalmente en la medida de Pástor-Stambaugh en el contexto del modelo tri-factorial de Fama-French y, más recientemente, en su nuevo modelo de cinco factores. En este artículo, se discuten las aportaciones anteriormente aludidas desde la perspectiva de errores en las variables. En particular, se proponen nuevos instrumentos robustos que se han desarrollado y aplicado en distintas etapas de nuestra investigación. En este artículo, se llevan a cabo los test de robustez de estos nuevos instrumentos. En general, nuestros nuevos instrumentos, con estimación GMM, muestran que tanto en el marco de sección cruzada o de datos panel como en una regresión recursiva/rolling regression (en comparación con el marco del filtro de Kalman) el factor más significativo es el factor de mercado. Estos resultados podrían interpretarse en la línea de la preocupación Cochrane acerca de un "zoológico de factores".

Palabras clave: GMM, momentos superiores, filtro de Kalman, iliquidez, instrumentos robustos, contraste de variables instrumentales débiles.

JEL Classification: C13, C23, G12

Artículo recibido en septiembre de 2017 y aceptado en noviembre de 2017 Artículo disponible en versión electrónica en la página www.revista-eea.net, ref. ə-36103

1. INTRODUCTION

The Fama and French (FF, 1992, 1993, 2015) models as well as the Pástor and Stambaugh (PS, 2003) extension are expressed in terms of unobservable expectations of the explanatory and dependent variables. In fact, however, estimates of these models use *realized* values of the variables. Essentially, these realizations are the expectations measured with error. So, *a priori*, using OLS to find the parameters of the FF or PS models would yield incorrect estimation. More precisely, when there are measurement errors¹, endogeneity, or more generally specification errors, the OLS estimator is inconsistent. Thus, a robust instrumental variables approach is strongly recommended when estimating financial models based on expected values. Also, the original PS illiquidity factor is a constructed variable estimator itself may remain unbiased (Pagan, 1984, 1986, and Pagan and Ullah, 1988²). The proposed methodology originally developed in Racicot (2015) and Racicot and Rentz (2015) that we review in this article will yield more robust inference in the presence of this type of explanatory variables.

A concern in the PS model is a possible relation between the PS illiquidity measure and the FF small firm anomaly variable (*SMB*), as small firms tend to be less liquid than large firms. This might create some specification error in the empirical PS model.

Since the seminal work of Frisch (1934), the treatment of specification errors, particularly endogeneity, is regarded as a challenging problem in empirical financial economics. Endogeneity, measurement errors, or more broadly, specification errors may lead to an inconsistent ordinary least squares (OLS) estimator and yield unreliable results. In the econometrics literature, specification errors generally lead to non-orthogonality between the regressors and the error term. Spencer and Berk (1981) conjecture that specification errors originate from many sources, such as omission of relevant regressors, errors in variables, inappropriate aggregation over time, simultaneity (endogeneity), and incorrect specification form. Traditionally, a Hausman (1978) test may be used to identify this problem. Among other things, we revisit a modified Hausman test of ours relying on robust instrumental variables may worsen the problem. Greene (2018, pp. 279-280) notes that the use of weak instruments may lead to "perverse and

¹ Shiller (2005, 2014) states that speculative bubbles may incur when price increases spur investor enthusiasm. Hence, observed prices are not always equilibrium prices and observed prices may be viewed as equilibrium prices with measurement errors.

² When the constructed variable is of the conditional variance type, the OLS estimator is biased.

contradictory results³." We review a procedure of ours that generates robust instruments that tackle the weak instrumental variables problem. Following Racicot and Rentz (2015), we mention a new robustness test-i.e., a weak instrumental variables test-based on an analogous version of the test discussed in Olea and Pflueger (2013) and the results appear promising.

Next, we discuss an extension of Racicot $(2015)^4$ that generalizes the GMM_d approach to a fixed and random effects panel data framework. In addition, we allow not only for the Jensen α performance measure to vary across sectors but also the β systematic risk measure to vary. This generalization enables us to (i) evaluate the robustness of the new five-factor FF (2015) model and (ii) compare this model to a six-factor model that incorporates the PS (2003) illiquidity risk factor. This empirical framework allows us to provide some new insights on the effects of unobserved heterogeneity in panel data models that may compound measurement errors if not tackled properly. One approach to removing unobserved heterogeneity is to rely on first-differencing. In fact, this may worsen the situation. Arellano (2003)⁵ shows that it is only by chance that the method of first-differencing in a panel data framework will diminish measurement errors.

Fama and MacBeth (1973) introduce a process for estimating cross-sectional regressions and standard errors correcting for cross-sectional correlation in a panel data framework. Cochrane (2005, p.245) shows that when the right-hand side variables are invariant through time, the Fama-MacBeth results are equivalent to (i) the pooled regression, (ii) cross-section OLS with standard errors corrected for cross-sectional correlations, and (iii) single cross-sectional regression on time series averages with standard errors corrected for crosssectional correlations. Shanken (1992) proposes a way to correct the bias in the estimation process for the standard errors caused by the two-pass regression approach. However, as Cochrane (2005) points out, one way to tackle these problems is to use the more powerful GMM approach. One of the virtues of our proposed generalized GMM_d panel data framework is a systematic treatment of the previous specification errors including the problem of measurement errors. To the best of our knowledge, we are the first to use panel data for both fixed and random effects models for testing the new FF model using the GMM_d approach (Racicot and Rentz, 2017b).

³ Nelson and Startz (1990a,b) and Hahn and Hausman (2003) list two important implications using weak instruments. (i) The 2SLS is badly biased towards the OLS estimator, and (ii) the standard first-order asymptotics will not give an appropriate framework for statistical inference.

⁴ See also Racicot and Rentz (2017a).

⁵ However, in a non-panel data framework, Dagenais (1994) shows when pseudo differencing is used to correct for autocorrelation as in the iterative method of Cochrane and Orcutt (1949), the problem of measurement errors is exacerbated.

Finally, we discuss our recasting of the new Fama-French (2015) into a dynamic framework based on Kalman filtering and the generalized method of moments (GMM) with robust instruments⁶. The Kalman filter may be regarded as a more scientifically rigorous process since it is the dual of the Bellman (1957) equation (Ljungqvist and Sargent, 2004). This is in line with Cochrane (2017) who notes that the FF (1993) factors are *ad hoc*. Cochrane (2011, 2017) also expresses concern about the "zoo of factors". For example, Harvey *et al.* (2016) list 316 variables in the literature. Harvey (2017) and Mclean and Pontiff (2016) caution that many of these factors may be spurious. The GMM approach is not naturally dynamic. To implement the recursive GMM in a time-varying framework, we recursively add one new observation of the FF factors at each iteration before estimating the model parameters. This approach is analogous to Kalman filtering without being based on a state-space optimization process. For a matter of comparison, we also compute a dynamic rolling GMM regression.

The remainder of this article is organized as follows. Section 2 discusses the FF five-factor model and its extension to include illiquidity. Section 3 presents an overview of our panel data approach while Section 4 briefly discusses our dynamic framework of the FF model. Section 5 presents our results, and Section 6 concludes.

2. THE NEW FAMA-FRENCH FIVE-FACTOR MODEL AND ILLIQUIDITY

Fama and French (FF, 1992, 1993) introduce their three-factor asset pricing model. The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) is known to have only modest explanatory power for individual equity returns⁷. To further refine their model, FF (2015) introduce two additional factors, profitability RMW_t and investment CMA_t , to create the following five-factor model⁸,

$$r_{it} - r_{ft} = \alpha_i + \beta_{1i} \left(r_{mt} - r_{ft} \right) + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} RMW_t + \beta_{5i} CMA_t + \varepsilon_{it}$$
(1)

where $r_{it} - r_{ft}$ is the excess return of sector *i*, $r_{mt} - r_{ft}$ is the market risk premium, and *SMB*_t and *HML*, are the small size and value anomalies.

The extended version of the FF model that accounts for illiquidity is written as

⁶ See Racicot, Rentz, and Kahl (2017b).

⁷ Several authors (e.g. Benninga, 2014) show that the explanatory power of the CAPM substantially improves when applied to a portfolio of equities.

⁸ See Racicot and Rentz (2016, 2017a) for a discussion of these new factors.

$$r_{it} - r_{ft} = \alpha_i + \beta_{1i} \left(r_{mt} - r_{ft} \right) + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} RMW_t + \beta_{5i} CMA_t + \beta_{6i} IML_t + \varepsilon_{it}$$
(2)

where IML_t is the difference in returns of a portfolio of illiquid and liquid assets as defined by Pástor and Stambaugh (PS, 2003). We select the PS measure because it is well recognized by practitioners (e.g., Pinto *et al.*, 2015). Fong *et al.* (2017) discuss several types of liquidity measures. They qualify the PS measure as a monthly cost-per-volume proxy. This class includes Amihud (2002) and the extended Amihud class of Goyenko *et al.* (2009). They also discuss ten extended Amihud proxies found in the literature.

3. PANEL DATA APPROACH

We extend (2) to a fixed effects panel data framework including the *IML* factor, written in stacked vector format for the 12 FF sectors (Racicot and Rentz, 2017a),

$$Y = R - R_F = \sum_{i=1}^{12} \alpha_i D_i + \sum_{i=1}^{12} \beta_i D_i \left(R_M - R_F \right) + s SMB + h HML + r RMW + c CMA + iILM + e$$
(3)

where $Y' = (R_{11} - R_{F1}, \dots, R_{1T} - R_{FT}, \dots, R_{12,1} - R_{F1}, \dots, R_{12,T} - R_{FT})$ represents the transpose of the stacked vector Y of excess returns for each sector; $D_i' = (0, \dots, 0, \dots, 1, \dots, 1, 0, \dots, 0)$ is the transpose of the stacked dummy variable, which is 0 everywhere, except for the T observations for sector i; α_i is the Jensen (1968) performance measure for sector i; and $(R_M - R_F)' = (R_{M1} - R_{F1}, \dots, R_{MT} - R_{F1}, \dots, R_{MT} - R_{FT})$ is the transpose of the stacked vector of excess market returns. That is, the excess market returns are stacked 12 times, once for each sector. β_i is the sector i CAPM systematic risk beta. The other explanatory variables are similarly defined. The coefficients of these other variables are 12-sector pooled coefficients. e is the stacked vector of error terms.

The fixed effects (FE) model may be implemented via a transformation into its mean deviations to obtain the covariance matrix, which is the basic least squares dummy variables (LSDV) model.

The standard random effects model⁹ allows the constant term to vary randomly while the generalized random effects model allows for all parameters to vary.

3.1. The new GMM_d approach for panel data

Our new GMM_d estimator written into a fixed effects panel data framework is given by (Racicot, 2015)¹⁰,

⁹ For more details on this subject, see Greene (2018) and Racicot and Rentz (2017b).

$$\hat{\theta}_{GMM_d} = \left[\left(\sum_{i=1}^{N} X_i \,' d_i \right) \hat{w}^{-1} \left(\sum_{i=1}^{N} d_i \,' X_i \right) \right]^{-1} \left[\left(\sum_{i=1}^{N} X_i \,' d_i \right) \hat{w}^{-1} \left(\sum_{i=1}^{N} d_i \,' Y_i \right) \right] \tag{4}$$

where $\hat{w} = \frac{1}{N^2} \sum_{i=1}^{N} d_i \, \hat{\xi}_i \, \hat{\xi}_i \, d_i$, ξ_{it} is the error term of the model in first difference form and $d_i = x_i - \hat{x}_i$ is a vector of robust "distance" instruments. These new instruments—the *d* "distance" instruments—can be computed using a matrixweighted average by applying GLS to a combination of two robust estimators, namely the Durbin (1954) and Pal (1980) estimators (Racicot, 2015). The asymptotic covariance matrix can be computed as $Est.Asy.V(\hat{\theta}_{GMM_d}) = \left[\left(\sum_{i=1}^{N} X_i \, d_i \right) \hat{w}^{-1} \left(\sum_{i=1}^{N} d_i \, X_i \right) \right]^{-1}$.

The generalized random effects version of our new GMM_d estimator can be computed by a weighted average of the sector GMM_d estimations as in Swamy (1970). Using his suggested weights is in fact a GLS estimator (Greene, 2018; Racicot and Rentz, 2017b).

3.2. Weak instrumental variable test

Weak instruments occur when $\left(\frac{1}{n}\right)Z'X$ is close to zero. We proceed analogously to Olea and Pflueger (2013) who extend the work of Stock and Yogo $(2005)^{11}$ and Stock and Watson (2011, ch. 12) to the more general case of heteroscedasticity and autocorrelation. These authors propose using the conventional *F* statistic for testing the joint significance of all the coefficients in the regression

$$x_i = z_i \,' \pi + v_i \tag{5}$$

This tests the hypothesis that the instruments are weak. In other words, this is a test of the relevance of the instruments. Specifically, we test each explanatory variable by running regression (5) on all of the instruments. According to Olea and Pflueger (2013) if the resulting F is below 24 for all of the regressions, this is a signal of a potential weak instruments problem.¹² If at

¹⁰ For the genesis of this technology, see Racicot (1993) or Dagenais and Dagenais (1994). Racicot (2014) develops the first application of this methodology for estimating the cost of equity (and the cost of capital) and provides some EViews code. Using this technology, Racicot and Théoret (2016) show how to estimate systemic risk in the hedge fund industry.

¹¹ See also Staiger and Stock (1997) for a similar test in the case of a large number of instruments.

¹² In theory, the *F* values could all be less than 24 and yet the instruments not be weak. Godfrey (1999) proposes a joint test on all of the explanatory variables. This test is not necessary here since *F* is greater than 24 for all 5 of our regressions.

least one of the *F* values is above 24, then at least one of the instruments is robust. In Racicot and Rentz (2015, Table 3) all *F* values are well over 24. The coefficients of the instrumental variables represent the partial correlation coefficients of the instruments with the explanatory variables. All the coefficients of the instrumental variables (*z*) on the corresponding dependent variables (*x*) in (5) are all close to 1 and have significant *t* values. The relevance test means that each individual instrument is highly related to its respective explanatory variable¹³.

4. A DYNAMIC FRAMEWORK FOR THE NEW AUGMENTED FAMA-FRENCH MODEL

The dynamic version of the augmented FF five-factor model is given by

$$r_{it} - r_{ft} = \alpha_{it} + \beta_{1it} \left(r_{mt} - r_{ft} \right) + \beta_{2it} SMB_t + \beta_{3it} HML_t + \beta_{4it} RMW_t + \beta_{5it} CMA_t + \beta_{6it} IML_t + \varepsilon_{it}$$
(6)

Note that α and β_1 are the dynamic versions of the performance and systematic risk measures of the heretofore static new FF model. Racicot, Rentz, and Kahl (2017b) investigate (6) using either Kalman filtering or a recursive/rolling regression approach. The Kalman filtering approach considers the pure random walk model first for both the performance and systematic risk measures. Then an analogous recursive/rolling regression approach is evaluated.

The recursive GMM_d formulation, which adds one observation at each iteration, of our robust instrumental variable estimator is as follows (Racicot, Rentz, and Kahl, 2017b):

$$\arg\min_{\hat{\beta}_{t}} \left\{ n^{-1} \left[d_{t} \left(Y_{t} - X_{t} \hat{\beta}_{t} \right) \right] W_{t} n^{-1} \left[d_{t} \left(Y_{t} - X_{t} \hat{\beta}_{t} \right) \right] \right\}$$
(7)

Except for the time-varying generalization, the variables in (7) are defined as in (4) above (unstacked). Note that the matrix of variables X at time t includes observations from 60-time periods in our rolling version of the regression.

5. RESULTS

The data to perform our estimations in Table 1 are from French's website for the FF 12 sectors monthly returns (January 1968-December 2015). The illiquidity measure that we use (IML) is from Pástor's website.

¹³ See Racicot and Rentz (2015) for more details.

| | | | | | _ | | | | | | | _ | | _ | |
|---------------------------------|------------|---------------------|---------|--------|--------|--------|--------|------------------------------|----------------------|----------------------|----------------------|---------------------------|----------------------|------------------|------|
| | c | $R_m - R_f$ | SMB | HML | RMW | СМА | IML | $\widehat{\omega}_{R_m-R_f}$ | $\hat{\omega}_{SMB}$ | $\hat{\omega}_{HML}$ | $\hat{\omega}_{RMW}$ | <i>̂</i> ⊕ _{CMA} | $\hat{\omega}_{IML}$ | \overline{R}^2 | DW |
| FF+IML Cross se | ctions | | | | | | | | | | | | | | |
| OLS | -0.0535 | 0.9932 | 0.0218 | 0.1090 | 0.1669 | 0.0748 | 0.0098 | | | | | | | 0.73 | 1.97 |
| t-mean | 1.79 | 38.63 | 4.48 | 4.62 | 5.74 | 2.21 | 1.79 | | | | | | | | ł |
| GMM _d | -0.1653 | 1.0148 | -0.0501 | 0.1697 | 0.1345 | 0.2242 | 0.1152 | | | | | | | 0.42 | 1.87 |
| t-mean | 1.25 | 4.59 | 0.42 | 0.71 | 0.71 | 1.18 | 0.88 | | | | | | | | ļ |
| # of signif. Indices | 1 | 11 | 0 | 0 | 0 | 3 | 0 | | | | | | | | ł |
| Haus _d | -0.0256 | 1.0148 | -0.0501 | 0.1697 | 0.1345 | 0.2242 | 0.1152 | -0.0232 | 0.0740 | -0.0790 | -0.0179 | -0.1632 | -0.1105 | 0.73 | 1.97 |
| Abs t-mean | 1.66 | 7.146 | 0.90 | 1.60 | 1.39 | 1.77 | 1.68 | 1.15 | 1.26 | 1.54 | 1.25 | 1.39 | 1.49 | | ł |
| # of signif indices | 3 | 12 | 1 | 4 | 3 | 5 | 4 | 2 | 2 | 3 | 2 | 4 | 3 | | ļ |
| FF+IML panel fixe | ed effects | | | | | | | | | | | | | | |
| OLS | -0.0535+ | 0.09932* | 0.0218 | 0.1090 | 0.1669 | 0.0748 | 0.0098 | | | | | | | | |
| t-stat | 1.03 | 35.83 | 1.68 | 6.08 | 8.96 | 2.69 | 0.95 | | | | | | | 0.69 | 1.94 |
| # of signif. indices | 2 | 12 | | | | | | | | | | | | | ļ |
| GMM _d | 0.1653† | 1.0148† | -0.0501 | 0.1697 | 0.1345 | 0.2242 | 0.1152 | | | | | | | 0.65 | 1.89 |
| t-stat | 1.99 | 7.77 | -0.39 | 0.79 | 0.52 | 1.20 | 1.34 | | | | | | | | ļ |
| # of signif. Indices | 2 | 12 | | | | | | | | | | | | | ļ |
| Haus _d | -0.0256+ | 1.0148 ⁺ | -0.0501 | 0.1697 | 0.1345 | 0.2242 | 0.1152 | -0.0232 | 0.0740 | -0.0790 | -0.0179 | -0.1632 | -0.1105 | 0.69 | 1.94 |
| t-stat | 0.99 | 11.76 | -0.61 | 1.52 | 0.85 | 1.86 | 2.46 | 1.16 | 0.89 | -0.69 | -0.11 | -1.32 | -2.30 | | |
| # of signif. indices | 1 | 12 | | | | | | | | | | | | | |
| FF+IML dynamic (rolling method) | | | | | | | | | | | | | | | |
| OLS | 0.06 | 0.97*** | 0.01 | 0.07 | na | na | 0.01 | | | | | | | | |
| GMM _d | 0.06 | 0.97*** | 0.02 | 0.09 | na | na | 0.01 | | | | | | | | |

 Table 1

 New Fama-French (FF) model estimations using FF 12 sectors (1968-2015)

Notes: The FF + IML cross sections of the table may also be found in Racicot and Rentz (2016). The FF + IML panel fixed effects of the table may be found in Racicot and Rentz (2017a). The FF + IML dynamic may be found in Racicot, Rentz, and Kahl (2017a).[†] represents the average of the coefficients obtained from the fixed effects model, which is also the pooled values. *** indicates significance at the 1% level. The average of the t-statistics (in italics) is computed from the absolute values. #t of signif. indices represent the number of significant FF sectors at the 5% or better level. $\hat{\omega}$ is the companion variable in the Hausman (1978) artificial regression, which tests for errors-in-variables or specification errors. A significant t-test for this variable indicates potential errors in the corresponding explanatory variable. na indicates not available at present time but for future research. The t-statistics for GMM_d are computed using the Newey and West (1987) HAC matrix. \mathbb{R}^2 is the adjusted R-squared and DW the Durbin-Watson statistic.

Source: Own elaboration.

Relying on OLS estimation, the augmented FF model seems highly significant both in terms of adjusted R^2 and individual *t*-statistics for the cross-sectional estimations¹⁴. However, when using our GMM_d estimator, the results are not quite so appealing. Only the market risk premium seems to matter. In addition, the same results are confirmed when using the panel data framework. One should not, however, draw conclusions too fast based on those facts by qualifying these results as pertaining to Cochrane's (2011, 2017) "zoo of factors"¹⁵. In particular, the Hausman regression (Haus_d in Table 1) suggests

¹⁴ More precisely, the estimates that we refer to as cross-sectional in Table 1 are based on individual time series for each sector and then the obtained parameters are averaged over the sectors.

¹⁵ Cochrane (2017) does not include the FF (1993) factors in the "zoo of factors". He does, however, qualify these factors as *ad hoc* factors. He also recognizes the importance of these factors but criticized the lack of a macro-finance modeling framework justifying these factors.

that the investment factor *CMA* and the illiquidity factor *IML* may well be significant. Furthermore, *IML* shows significant measurement errors. This is consistent with our conjecture that at least both the risk premium and the illiquidity factors may well be measured with errors. Note also that in its original formulation, the illiquidity factor may qualify as a constructed variable (Pagan, 1984, 1986) therefore leading to biased inferences (i.e., biased *t*-statistics). These facts may justify our GMM_d/Haus_d approach.

Cochrane (2017) does not comment on the new Fama-French (2015) profitability *RMW* and investment *CMA* factors. However, we do believe that FF (2015) made a significant effort to provide a theoretical basis for these new factors as proxies for Tobin's (1969) q. Hou *et al.* (2015) provide further evidence of this. We, therefore, believe that the model might well be useful in explaining returns. It should not be dismissed and may be considered as a complement to the theoretically well-grounded CAPM.

6. CONCLUSIONS

Intuitively, illiquidity should matter with respect to investment returns. A major issue is how do you measure illiquidity. Based on recent literature (e.g. Fong *et al.*, 2017), there is a plethora of proxy measures. Since these are proxies, they are likely to be prone to measurement errors. Measurement errors that are random are well known to bias the OLS estimator.

Two contributions of this survey paper are to (i) account for illiquidity in the new Fama-French (2015) model and (ii) propose a way to tackle these errors-in-variables/specification errors based on robust instruments in conjunction with the well-known GMM estimator.

We show that when using our new estimator that the new augmented FF model does not seem to be significant in our experiment. However, when relying on another approach of ours (i.e., Haus_d), some of the new FF factors including illiquidity do seem to matter. We, therefore, conclude that the new Fama-French *RMW* and *CMA* factors may not fall into Cochrane's (2011, 2017) "zoo of factors" and may be a good complement to the theoretically well-grounded CAPM.

BIBLIOGRAPHY REFERENCES

AMIHUD, Y. (2002). "Illiquidity and stock returns: Cross-section and time-series effects". *Journal of Financial Markets*, 5, pp. 31-56.

ARELLANO, M. (2003). *Panel Data Econometrics*. Oxford: Oxford University Press. BELLMAN, R. (1957). *Dynamic Programming*. Princeton, NJ: Princeton University Press.

BENNINGA, S. (2014). Financial Modeling. 4th ed. Cambridge, MA: MIT Press.

- COCHRANE, D. and ORCUTT, G. (1949). "Application of the least squares regression to relationships containing autocorrelated error terms". *Journal of the American Statistical Association*, 44, pp. 32-61.
- COCHRANE, J. H. (2005). Asset Pricing. Revised ed. Princeton, NJ: Princeton University Press.
- COCHRANE, J. H. (2011). "Presidential address: Discount rates". *Journal of Finance* 66 (4), pp. 1047-1108.

COCHRANE, J. H. (2017). "Macro-finance". Review of Finance, 21(3), pp. 945-985.

- DAGENAIS, M. G. (1994). "Parameter estimation in regression models with errors in the variables and autocorrelated disturbances". *Journal of Econometrics*, 64(1), pp. 145-163.
- DAGENAIS, M. G. and DAGENAIS, D. L. (1994). "GMM estimators for linear regression models with errors in the variables". Centre de Recherche et Développement en Économique (CRDE), Working Paper 0594, Montreal, QC: University of Montreal.
- DURBIN, J. (1954). "Errors in variables". International Statistical Review, 22, pp. 23-32.
- FAMA, E. F. and FRENCH, K. R. (1992). "The cross-section of expected stock returns". *Journal of Finance*, 47, pp. 427-465.
- FAMA, E. F. and FRENCH, K. R. (1993). "Common risk factors in the returns on stocks and bonds". *Journal of Financial Economics*, 33, pp. 3-56.
- FAMA, E. F. and FRENCH, K. R. (2015). "A five-factor asset pricing model". *Journal of Financial Economics*, 116, pp. 1-22.
- FAMA, E. F. and MacBeth, J. D. (1973). "Risk, return, and equilibrium: Empirical tests". *Journal of Political Economy*, 81(3), pp. 607-635.
- FONG, K. Y. L., HOLDEN, C. W., and TRACINKA, C. A. (2017). "What are the Best Liquidity Proxies for Global Research?". *Review of Finance*, 21(4), pp. 1355-1401.
- FRISCH, R. (1934). "Statistical confluence analysis by means of complete regression system". University Institute of Economics, Oslo.
- GODFREY, L. (1999). "Instrument relevance in multivariate linear models". *Review of Economics and Statistics*, 81, pp. 550-552.
- GOYENKO, R., HOLDEN, C., and TRZCINKA, C. (2009). "Do Liquidity Measures Measure Liquidity?" *Journal of Financial Economics*, 92, pp. 153-181.

GREENE, W. H. (2018). *Econometric Analysis*. 8th ed. Boston, MA: Pearson.

- HARVEY, C.R., LIU, Y., and ZHU, H. (2016). "... and the cross-section of expected returns". *Review of Financial Studies*, 29, pp. 5-68.
- HARVEY, C. R. (2017). "Presidential address: The scientific outlook in financial economics". *Journal of Finance*, forthcoming.
- HAHN, J. and HAUSMAN, J. (2003). "Weak instruments: Diagnosis and cures in empirical economics". *American Economic Review*, 93, pp. 118-125.
- HAUSMAN, J. A. (1978). "Specification tests in econometrics". *Econometrica*, 46, pp. 1251-1271.
- HOU, K., XUE, C., and ZHANG, L. (2015). "Digesting anomalies: An investment approach". *Review of Financial Studies*, 28, pp. 650-705.
- JENSEN, M. C. (1968). "The performance of mutual funds in the period 1945-64". *Journal of Finance*, 23, pp. 389-416.

- LINTNER, J. (1965). "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets". *Review of Economics and Statistics*, 46, pp. 13-37.
- LJUNGQVIST, L., and SARGENT, T. J. (2004). *Recursive Macroeconomic Theory*. 2nd ed. Cambridge, MA: MIT Press.
- MCLEAN, R. D. and PONTIFF, J. (2016). "Does academic research destroy stock return predictability?" *Journal of Finance*, 71, pp. 5-32.
- MOSSIN, J. (1966). "Equilibrium in a capital asset market". *Econometrica*, 34, pp. 768-783.
- NELSON, C. and STARZ, R. (1990a). "The distribution of the instrumental variables estimator and its *t*-ratio when the instrument is a poor one". *Journal of Business*, 63(1), pp. 125-140.
- NELSON, C. and STARZ, R. (1990b). "Some further results on the exact small sample properties of the instrumental variable estimator". *Econometrica*, 58(4), pp. 967-976.
- NEWEY, W. K. and WEST, K. D. (1987). "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix". *Econometrica*, 55, pp. 703-708.
- OLEA, J. L. M. and PLUEGER, C. (2013). "A robust test of weak instruments". *Journal of Business and Economic Statistics*, 31(3), pp. 358-369.
- PAGAN, A. R. (1984). "Econometric issues in the analysis of regressions with generated regressors". *International Economic Review*, 25, pp. 221-247.
- PAGAN, A. R. (1986). "Two stage and related estimators and their applications". *Review of Economic Studies*, 53, pp. 517-538.
- PAGAN, A. R. and Ullah, A. (1988). "The econometric analysis of models with risk terms". *Journal of Applied Econometrics*, 3, pp. 87-105.
- PAL, M. (1980). "Consistent moment estimators of regression coefficients in the presence of errors in variables". *Journal of Econometrics*, 14, pp. 349-364.
- PÁSTOR, L. and STAMBAUGH, R. F. (2003). "Liquidity risk and expected stock returns". *Journal of Political Economy*, 111, pp. 642-685.
- PINTO, J. E., HENRY, E., ROBINSON, T. R., STOWE, J. D., and WILCOX, S. E. (2015). *Equity Asset Valuation*. 3rd ed., New York: John Wiley & Sons.
- RACICOT, F. E. (1993). "Techniques alternatives d'estimation et tests en présence d'erreurs de mesure sur les variables explicatives". M.Sc. thesis, Department of Economics, University of Montreal.
- RACICOT, F. E. (2014). "Erreurs de mesure sur les variables économiques et financières". *La Revue des Sciences de Gestion*, 267-268 (3-4), pp. 79-103.
- RACICOT, F. E. (2015). "Engineering robust instruments for panel data regression models with errors in variables: A note". *Applied Economics*, 47, pp. 981-989.
- RACICOT, F. E. and RENTZ, W. F. (2015). "The Pástor-Stambaugh empirical model revisited: Evidence from robust instruments". *Journal of Asset Management*, 16(5), pp. 329-341.
- RACICOT, F. E. and RENTZ, W. F. (2016). "Testing Fama-French's new five-factor asset pricing model: Evidence from robust Instrumental variables". *Applied Economics Letters*, 23(6), pp. 444-448.

- RACICOT, F. E. and RENTZ, W. F. (2017a). "A panel data robust instrumental variable approach: A test of the new Fama-French five-factor model". *Applied Economics Letters*, 24(6), pp. 410-416.
- RACICOT, F. E. and RENTZ, W. F. (2017b). "Estimating panel data fixed and random effects with application to the new Fama-French model using GMM robust instruments". unpublished working paper, Telfer School of Management, University of Ottawa.
- RACICOT, F. E., RENTZ, W. F., and KAHL, A. L. (2017a). "Rolling regression analysis of the Pástor-Stambaugh model: Evidence from robust instrumental variables". *International Advances in Economic Research*, 23(1), pp. 75-90.
- RACICOT, F. E., RENTZ, W. F., and KAHL, A. L. (2017b). "Testing illiquidity risks in the phases of the business cycle with the new five-factor Fama and French model." unpublished working paper, Telfer School of Management, University of Ottawa.
- RACICOT, F. E. and THÉORET (2016). "Macroeconomic shocks, forward-looking dynamics, and the behavior of hedge funds". *Journal of Banking and Finance*, 62, pp. 41-61.
- SHANKEN, J. (1992). "On the estimation of beta-pricing models". *Journal of Finance*, 47, pp. 1-34.
- SHARPE, W. F. (1964). "Capital asset prices: A theory of market equilibrium under conditions of risk". *Journal of Finance*, 19, pp. 425-442.
- SHILLER, R. J. (2005). *Irrational Exuberance*, 2nd ed., Princeton, NJ: Princeton University Press,
- SHILLER, R. J. (2014). "Speculative asset prices". Cowles Foundation Discussion Paper No. 1936, Yale University.
- SPENCER, D. E. and Berk, K. N. (1981). "Limited information specification test". *Econometrica*, 49, pp. 1079-1085.
- STAIGER, D. and STOCK, J. H. (1997). "Instrumental variables regression with weak instruments". *Econometrica*, 65, pp. 557-586.
- STOCK, J. H. and WATSON, M. W. (2011). *Introduction to Econometrics*, 3rd ed., Boston, MA: Pearson.
- STOCK, J. H. and Yogo, M. (2005). "Testing for weak instruments in linear IV regression". In: Andrews, W. K., and Stock, J. H. (ed.): *Identification and Inference in Econometric Models: Essays in Honor of Thomas J. Rothenberg* (ch. 5). Cambridge, England: Cambridge University Press.
- SWAMY, P., (1970). "Efficient inference in a random coefficient regression model", *Econometrica*, 38, pp. 311-323.
- TOBIN, J. (1969). "A general equilibrium approach to monetary theory". *Journal of Money, Credit, and Banking*, 1(1), pp. 15-29.