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IES Working Paper 13/2020

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Bibliographic information:
Brakatsoulas P. and Kukacka J (2020): "Credit Rating Downgrade Risk on Equity Returns" IES Working Papers 13/2020. IES FSV. Charles University.

This paper can be downloaded at: http://ies.fsv.cuni.cz

Credit Rating Downgrade Risk on Equity Returns

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May 2020

Abstract:
We develop a four-factor model intended to capture size, value, and credit rating transition patterns in excess returns for a panel of predominantly mid- and large-cap entities. Using credit transition matrices and rating histories from 48 US issuers, we provide evidence to support a statistically significant negative downgrade risk premium in excess returns, suggesting that stocks at higher risk of failure tend to deliver lower returns. The performance of the model remains robust across several estimation methods. Panel Granger causality test results indicate that there indeed is a Granger-causal relationship from credit rating transition probabilities to excess returns. Our paper thus provides a new methodology to generate firm-level downgrade probabilities and the basis for further empirical validation and development of Fama-French-type models under financial distress.

JEL: G11, G12, G14, G41
Keywords: Asset pricing, credit risk, panel data, stock returns, transition matrices.

1. Introduction

A large body of empirical work has put in doubt the ability of accounting data to explain equity prices (Lev and Zarowin, 1999; Francis and Schipper, 1999; Hillegeist et al., 2004; Agarwal and Taffler, 2008a; Tinoco and Wilson, 2013). A new class of models (Vassalou and Xing, 2004; Chan-Lau, 2006; Anginer and Yildizhan, 2010; Chava and Purnanandam, 2010; Friedwald et al., 2014) relies exclusively on market data, using option pricing methods and debt/credit market securities, to measure the probability of default (PD). While there is strong theoretical and empirical evidence that market-price indicators are effective at corporate bankruptcy prediction, the question of whether and how systematic credit risk is associated with equity returns remains open. More important, the results remain inconclusive as to the method we should use to measure distress in the presence of market failures.

In this paper, we use a new methodology to generate firm-level downgrade probabilities and build upon the Fama and French (1993) description of average stock returns. To address the relationship between stock excess returns and downgrade risk, we use data on 48 predominantly mid- and large-cap NYSE entities over the period 2012Q1-2018Q4. We believe that this is the first work converting credit transition matrices into firm-level PD to price downgrade risk. Our method requires individual corporate ratings and credit transition matrices to calculate the conditional probability of an asset downgrading, including default. Finally, the new PD captures the distress effect and suggests that momentum does not necessarily concentrate amongst small illiquid stocks.

The FF three-factor model has long been a basic tenet of finance. The authors suggest that cross-sectional differences in excess returns depend not only on market risk (Sharpe, 1964; Lintner, 1965) but also on firm-level market capitalization (size) and book-to-market (value). Empirical research has since focused on similar model variants, identifying various asset pricing anomalies, and thereby new pricing factors. To capture short-term momentum effects in US equity fund risk-adjusted returns, Carhart (1997) extends the FF three-factor model with a momentum factor defined as the difference between returns on value-weighted portfolios performing across the highest and lowest 30 percent of the sample. Randolph et al. (2002) examine the reaction of institutional trading to cash-flow news. They define cash-flow news as the change in the predicted long-run log price, driven by shocks to stock returns, profitability, the book-to-market ratio, and institutional ownership. The findings suggest that institutions respond to positive cash-flow news and subsequent high expected returns by buying shares from individual investors. Pastor and Stambaugh (2003) investigate whether expected returns relate to systematic liquidity risk in returns. They show that stocks exhibiting greater sensitivity to aggregate liquidity earn abnormal returns, even when accounting for exposures to market risk, size, value, and momentum factors. Titman et al. (2004) test whether stock portfolios with low abnormal capital investments demonstrate significantly higher returns than those with high abnormal capital investments. Their study suggests a strong negative relation between increased capital expenditures and subsequent returns for firms with higher cash flow-to-debt ratios and only when hostile takeovers appear to be less frequent.

Fama and French (2008) investigate various return anomalies such as size, momentum, growth, value, accruals, net stock issues, and profitability using cross-sectional regressions estimated across microcaps, small stocks, and large stocks. According to the results, both net stock issues and momentum provide strong coefficients for all size groups. The size effect is prominent in the case of microcaps and marginal among small and large portfolios. However, the relation between momentum and average stock returns for small and large stocks appears twice as strong as for microcaps. In the case of stock returns and asset growth, the relation is strong among microcaps and weak but still significant among small stocks. The book-to-market ratio, accruals, net stock issues, and profitability produce similar coefficients across groups suggesting that all four variables capture unique information about average returns. Novy-Marx (2013) finds that expected profitability is significantly related to stock returns and dramatically increases the performance of value strategies among the largest, most liquid, stocks. Similar to Randolph et al. (2002), Titman et al. (2004), and Fama and French (2008), Aharoni et al. (2013) identify a weak but statistically significant relation between investment and average returns. Using the dividend discount model (DDM) as a theoretical starting point, Fama and French (2015) add profitability and investment factors to the original three-factor model and argue that controlling for additional variables such as the momentum factor will likely result in poor diversification of some portfolios due to rising correlations among the five variables. While empirical evidence across international capital markets suggests that the FF five-factor model performs better than the three- and four-factor alternatives (Hou et al., 2015), it fails to capture momentum anomalies and low average returns on stocks with low operating profitability and high investment activity (Chiah et al., 2016; Fama and French, 2017; Foye, 2018).

Chan and Chen (1991) note that small portfolios are heavily populated by marginal firms with low market value, poor performance, high financial leverage, and cash flow constraints. They are marginal in the sense that their stock prices are subject to economic conditions and are therefore less likely to survive adverse economic scenarios. Vassalou and Xing (2004) argue that financially distressed stocks tend to deliver higher risk, which reflects the company's elevated probability of bankruptcy and corresponds to a positive premium in exchange for holding the asset. The author uses Merton's option pricing model (Merton, 1974) to compute each firm's distance-to-default and then convert it into a PD. Chava and Purnanandam (2010) employ both Merton's model (Merton, 1974) and the hazard rate estimation methodology, which utilize historical bankruptcy data, to obtain the maximum likelihood estimate of the PD (Shumway, 2001; Chava and Jarrow, 2004; Campbell et al., 2008). The authors again conclude in favour of a strong positive relationship between default risk and expected stock returns. Similarly, Chan-Lau (2006), Anginer and Yildizhan (2010), and Friedwald et al. (2014) apply the risk-neutral, that is, the risk-adjusted PDs and conclude that default risk is positively related to expected returns.[1] Empirical evidence is still inconclusive, however, as to the sign of the relation between default risk and realized returns: several empirical studies identify a negative relation between firms' real-world default probabilities and stock returns. George and Hwang (2010a) compute O-score dummies (Ohlson, 1980) using accounting data and estimate an index of distress intensity. They contend that firms with greater exposure to systematic default risk choose low leverage, which in turn reduces their physical/actual PDs, thus causing a negative relation between PDs and returns. Kapadia (2011) proposes a covariance-based approach (Lamont, 2001) to estimate the distress risk premium. Using data on aggregate business failures of both private and public firms, he forms portfolios maximally correlated with changes in expected business failure rates. The author again reports similar findings and argues that aggregate distress exposure is unrelated to low returns of high PD stocks. The negative distress premium puzzle is concentrated among small, illiquid stocks, suggesting that firms exhibiting greater distress intensities earn less (Griffin and Lemmon, 2002; Da and Pengjie, 2010; Garlappi and Yan, 2011). Similarly, Avramov et al. (2009b) convert long-term domestic issuer credit ratings into conventional numerical scores and capture a negative relation between credit risk and future returns.

[1] An important limitation here is that risk-neutral probabilities require individual security prices.

Both stands of the literature above measure default risk using either market-based (Merton, 1974) or accounting-based/physical (Altman, 1968; Ohlson, 1980; Campbell et al., 2008) PDs, implicitly assuming a positive monotonic relation between physical PDs and aggregate default risk. Nevertheless, PDs calculated using actual default frequencies may not necessarily account for exposure to systematic risk. The class of models that rely exclusively on market data to price distress has challenged PD estimates that utilize accounting data. Structural models use option pricing methods to compute PD from the level and volatility of the asset's market value, and reduced-form models derive default intensity from debt/credit market securities (Das et al., 2009). Both approaches yield default metrics that appear to perform better at forecasting distress than the Altman (1968) Z- or Ohlson (1980) O-score using a large sample of bankruptcies (Hillegeist et al., 2004). Although market-based default metrics are now widely popular among investors, accounting information remains essential to predict distress. Specifically, stock price drops will likely be reflected much faster in market-based PDs than physical PDs due to the delay in rating agencies' downgrading of company debt. Conversely, artificially high prices will distort downward-trending market-based PDs faster than accounting-based PDs. Conditioning on information not captured by physical PDs is therefore meaningful under efficient market hypothesis (EMH) violations.

Financial distress risk is commonly suggested as an underlying cause of several cross-sectional return anomalies. Chan and Chen (1991) attribute the size premium to the prevalence of small-cap stocks with poor performance, high financial leverage, and cash flow problems. Fama and French (1992) suggest financial distress risk as a potential explanation for the value premium. More recently, Agarwal and Taffler (2008b) demonstrate that both momentum and market mispricing of distressed firms are driven by market underreaction to financial distress risk. Furthermore, traditional asset pricing models do not fully account for distress premia. The capital asset pricing model (CAPM) fails to completely capture distress-risk premia when corporate failures correlate with deterioration in investment opportunities (Merton, 1973), unmeasured components of wealth such as human capital (Fama and French, 1996), and debt securities (Ferguson and Shockley, 2003). Similar to Lakonishok et al. (1994), Campbell et al. (2008) document a negative relation between various measures of default risk and realized stock returns and argue that the three-factor model overstates the average returns in many cases because it fails to account for distress premia. Moreover, the FF five-factor model, does not clarify whether firms with high profitability or low investment earn more due to higher distress risk or mispricing. While several studies identify the distress anomaly among small, illiquid stocks, there is no clear outcome of the effect on mid- and large-cap stocks. This paper extends the aforementioned literature using default probabilities to proxy for distress intensities and examine the relation between downgrade risk and excess returns. We find that the new risk factor reflects systematic risk exposure and remains surprisingly robust across medium-sized and large firms.

Despite a few exceptions, panel data studies testing the three-factor model and its extensions remain limited. Using various factor characteristics, Haugen and Baker (1996) demonstrate that stocks with higher expected and realized return rates exhibit lower risk than stocks with lower returns. Brennan et al. (1998) investigate the relation between stock returns and several risk and non-risk security characteristics, and provide evidence of return momentum, size, and book-to-market effects, together with a significantly negative relation between stock returns and trading volume. Cavaglia and Moroz (2002) provide a middle ground between traditional portfolio allocation and pure security selection methods using a cross-industry, cross-country allocation framework for global equity investment decisions. The authors argue that measures of profitability, value, and price momentum are significant determinants of asset price performance. The previous studies rely on the Fama and MacBeth (1973) procedure that estimates the structural parameters cross-sectionally and for every time snapshot in the data. The above procedure becomes unreliable with typical panel features such as individual effects that are firm specific rather than time specific. Chang et al. (2016) employ decile portfolios stratified by size, book-to-market, and momentum to estimate various multi-factor FF versions and conclude that the three- and four-factor FF models cannot fully account for the size, value and momentum premia, while the three-factor model is rejected in the case of small firms with a low book-to-market ratio. Makwasha et al. (2019) demonstrate that the market, size, and value risk exposures are significant and robust across three-, five- and six-factor panel models. Portfolio return forecasts generated by the six-factor model appear to be superior due to the inherent momentum factor explaining large return variations and volatility exposures.

The paper proceeds as follows: Section 2 describes the proxy measures for all risk factors in the model. The paper's methodological approach is presented in Section 3. Section 4 discusses the empirical results obtained and Section 5 provides concluding comments.

2. Data Overview and Construction

The data cleaning and quality assessment process primarily focused on entities with extensively populated observation histories. In that regard, note that large data gaps are apparent in the raw data set pre-2012. We thus consider history from and including 2012Q1, exclusively. In addition, entities missing two or more subsequent observations post-2012Q1 were also dropped. Finally, due to limited data availability for corporate ratings, along with the rich variable set requirements of the modeling exercise, a further drop in entities resulted in 28 quarterly observations (2012Q1-2018Q4) of 48 US companies listed on the NYSE (4 small-, 24 mid, and 20 large-cap stocks). The sample period finally decreases to 27 consecutive observations, since calculating the rate of return will exclude the first observation for each stock. The source for all factors related to size (price times shares outstanding), book-to-market equity (B/M), and credit ratings is Moody's proprietary senior unsecured ratings and corporate metrics (Moody's, 2019). The data also include information about the issuer industry. To proxy for the risk-free return, we employ short-term interest rates based on three-month money market rates provided by the OECD (OECD, 2019). We also use the NYSE composite index provided by Thomson Reuters to calculate the return on the value-weighted market portfolio (Thomson Reuters, 2019).

To calculate rating transition probabilities we classify all corporate entities into 7 broad categories: banking, capital, consumer, media-publishing, retail distribution, technology, and transportation. The rating categories are listed in decreasing order of rating quality as Aaa, Aa1, Aa2, Aa3, A1, A2, A3, Baa1, Baa2, Baa3, Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca, and C. We define C as the default category. Ratings Aaa to Baa3 represent the prime rating categories. Categories Aaa to A3 reflect issuers having superior ability to repay short-term debt obligations, categories Baa1 to Baa3 reflect issuers having strong or acceptable ability to repay short-term obligations, and any category below Ba1 reflects nonprime issuers.

Figure 1 reports changes in credit rating labels in each quarter as a percentage of the total number of stocks. The dynamics of fluctuations in credit quality for individual firms might appear sluggish in the sense that credit rating upgrades or downgrades are rather rare. This is because the sample consists predominantly of prime rating categories that exhibit less volatile behavior, and most of the firms experience two to three changes in credit standing between 2012 and 2018.

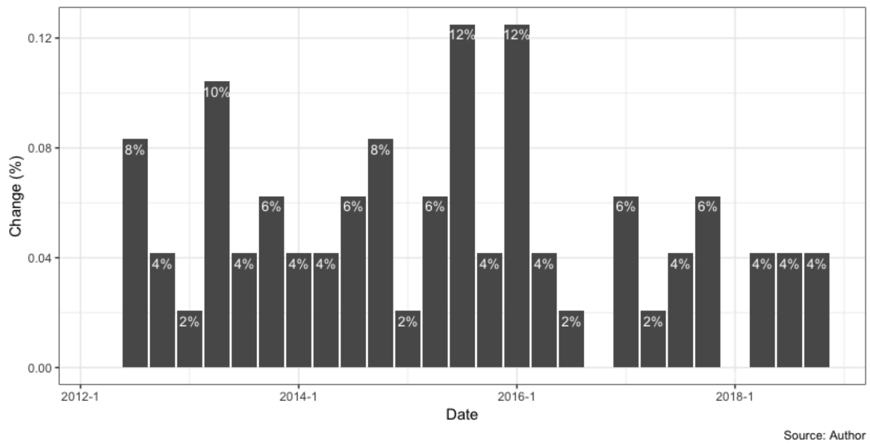


Figure 1: Rating Changes (%) over Time

However, the joint dynamics of firms' credit ratings generate sufficient variability to identify a significant effect of downgrade risk.

Following Fama and French (1993), we rank assets on size and B/M. In particular, using portfolio size medians grouped by time t, we split stocks into small (S) and large (B) groups. The B/M breakpoints are the bottom 30 (Low), middle 40 (Medium), and top 30 (High) percentiles of the ranked book-to-market values for all stocks at t. Next, we calculate quarterly value-weighted returns (VW) for the six portfolios (SL, SM, SH, BL, BM, BH) from 2×3 sorts on size and B/M as follows:

$$VW_{i,t} = P_{i,t-1}R_{i,t} / \sum_{k=1}^{K}\sum_{t=1}^{T} P_{i,t-1}, \tag{1}$$

where $P_{i,t-1}$ is the lagged price for $i = 1, 2, ...n$ shares, $n = 48$, $k = 1, 2, ...K$ is the k^{th} stock portfolio formed on size and B/M, and R is the stock return calculated as $(P_t/P_{t-1}) - 1$. We obtain stock prices by dividing the asset market value by outstanding shares. To calculate the difference between average returns on small (SL, SM and SH) and large (BL, BM and BH) portfolios (SMB) having the same weighted-average B/M, or high-B/M (SH and BH) and low-B/M (SL and BL) portfolios (HML) having the same weighted-average size, we use (2) and (3) below for each quarter t.

$$SMB_t = \sum_{t=1}^{T}[(VW_{i,t}^{SL} + VW_{i,t}^{SM} + VW_{i,t}^{SH}) - (VW_{i,t}^{BL} + VW_{i,t}^{BM} + VW_{i,t}^{BH})]/3 \tag{2}$$

$$HML_t = \sum_{t=1}^{T}[(VW_{i,t}^{SH} + VW_{i,t}^{BH}) - (VW_{i,t}^{SL} + VW_{i,t}^{BL})]/2 \tag{3}$$

3. Methodology

To calculate the probability of an upgrade or downgrade across credit scores and form rating transition statistics over credit condition changes, we build 27 quarterly cohort transition matrices for the 7 separate industries using rolling-average flow rates provided by Moody's. Hence, two issuers having the same attributes (current status, former status, rating outlook) will generate different transition probabilities in the same economic scenario. Rating transitions are calculated using the total number of US-based corporations reporting long-term ratings over a given period. The number varies over time and across industries.

Assuming that we obtain $N-1$ rating categories (excluding defaults) sorted in a descending order, we then observe $N-1$ historical average transition rates while the Nth value results from the condition that the probabilities equal 1. The total number of migration events observed over 1 period form a $(N-1)\times N$ matrix following (4) below.

$$(e_{i,1}, e_{i,2}) \in \{1, ..., N-1\} \times \{1, ..., N\} \tag{4}$$

Therefore, e_{i1} denotes the ratings status for entity i at the beginning and e_{i2} at the end of each quarter. Subsequently, similar migration events are aggregated in a $(N-1)\times N$ matrix M of transition counts, where the generic element m_t^{Gg} is the number of rating transitions from grade G to grade g observed at t.[2]

$$m_t^{Gg} = \sum_{i=1}^{n} 1\{(e_{i1}, e_{i2}) = (G, g)\} \tag{5}$$

The corresponding average G-to-g transition probability over a given horizon t equals the total number of entities with a certain initial rating G transitioning to any other rating status g at t divided by the number of entities assigned to G at $t-1$.

$$Pr_t^{Gg} = \sum_{G=1}^{N-1}\sum_{g=1}^{N} m_t^{Gg} / \sum_{G=1}^{N-1} m_{t-1}^{G} \tag{6}$$

By using historical average transition probabilities, we account for an underlying, discrete-time estimate of the cumulative change in creditworthiness over a given horizon with a standard normal distribution (Gupton et al., 1997). Transition dynamics are calculated in a discrete-time setting assuming time homogeneity. The probability for entity i to migrate from states G to g at time t is calculated by dividing the number of migrations from G to g at t by the total number of firms in state G at $t-1$. G to g transitions are coded as sequences of integers. An issuer, for example, currently rated Aa1 can transition to Aaa conditional on a credit rating upgrade, or any other rating state conditional on a credit rating downgrade. Conditional on credit rating G at t, we partition the estimates into quantile rating bands. We then define the bands such that the probability of G moving towards any given interval equals the corresponding average t-period

[2] $1\{.\}$ is the indicator function being equal to one if the logical expression in parentheses is true and zero otherwise.

transition rate (6). The final downgrade probability factor Pr^D, calculates the difference between a stock's individual probability of downgrading and the mean probability of downgrading across stocks grouped by time and the 2×3 portfolio sorts on size and B/M.

$$Pr_{i,t}^D = Pr_{i,t}^W - \sum_{t=1}^{T}\sum_{k=1}^{K} Pr_{t,k}^W / n \tag{7}$$

where $Pr_{i,t}^W = 1 - Pr_{i,t}^B$ is the individual probability of an asset downgrading and $Pr_{i,t}^B$ is the probability of remaining in the same rating category or upgrading.

Equation (8) models excess market return using mimicking returns for size and B/M factors and rating transition probabilities to proxy for common risk factors in stock returns. RF below is the risk-free asset return proxied by the US short-term interest rate, $R - RF$ the excess stock return, RM the total market portfolio return, $RM - RF$ the excess market return, Pr the probability of downgrade or credit quality deterioration for an asset, and e contains the unobserved individual-specific time-varying term and the error term ϵ.

$$R_{i,t} - RF_t = \beta_0 + \beta_1(RM_t - RF_t) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Pr_{i,t}^D + e_{i,t} \tag{8}$$

The two-stage regression of Fama and MacBeth (1973) is a common way of testing how risk factors explain excess returns. However, the previous method refers to cross-sectional factor models whereas the FF three-factor approach refers to time-series factor models. Provided that three out of four risk factors in the model vary only over time and not over units, the Fama-MacBeth cross-sectional regressions would be impractical. Moreover, the procedure accounts for error cross-sectional dependence but ignores time-series variation. Given the previous limitations and the short time dimension and to control for unobserved, time-varying, heterogeneity, we choose panel data analysis.

Error cross-sectional dependence can lead to misleading conclusions under standard estimation approaches. Since ordinary least squares (OLS) does not capture individual-specific heterogeneity, following the Hausman test, we estimate (7) using random effects (RE). (7) becomes an RE model by subsuming into the disturbance term an unobserved individual-specific random effect, μ_i, where $\mu_i \sim IID(0, \sigma_\mu^2)$, $\epsilon_{i,t} \sim IID(0, \sigma_\epsilon^2)$, μ_i is independent of $\epsilon_{i,t}$ and each explanatory variable is independent of the μ_i and $\epsilon_{i,t}$ for all i and t. Panel data estimates based on random or fixed effects impose, however, common coefficients across units, give no consideration to cointegration, and assume stationary data. In addition, they focus on short time horizons and become inconsistent as n and T increase (Pesaran and Smith, 1995). To address the abovementioned problems, we adopt a multifactor error structure, where cross-sectional correlation is modeled using time-variant unobservables. The Pesaran and Smith (1995) mean group (MG) approach allows a different set of estimates across panel units and calculates the final estimate as the unweighted mean of the individual regressions on each firm. Thus, we estimate (8) for each individual member i, including an intercept to capture fixed effects and a linear trend γ_i to capture time-variant unobservables. Serving as an alternative, the MG estimator is the Fama-MacBeth estimator swapping the group and time indices. Finally, the general feasible generalized least squares (FGLS) model follows a two-stage estimation process. We first estimate the model with RE, where the residuals are used to estimate an error variance–covariance matrix. The latter is then used to form consistent FGLS estimators. Note that the above procedure posits an unrestricted error covariance construction within respective groups of observations. This in turn provides robustness against any type of intragroup heteroskedasticity and serial and/or cross-sectional correlation (Wooldridge, 2010; Cameron and Miller, 2015).

In line with Fama and French (1993), Titman et al. (2004) and Novy-Marx (2013), a large body of empirical work follows a nonparametric approach by mimicking portfolios for risk factors in returns. Each of these X factors would be classified into K dimensional sorts times L different industries, leading to LK^X portfolios and parameters. While the potential number of X grows, portfolio formation strategies become infeasible, since we would quickly exhaust all degrees of freedom. Berk (2000) and Ferson et al. (2003) also emphasize that the particular portfolio strategy is subject to potential data-snooping biases. Sorting stocks according to characteristics that appear to correlate with returns in the sample can embed spurious risk premia. We therefore choose not to employ portfolio sorts and focus instead on the model's performance per se and the link between excess returns and downgrade risk in terms of credit transition dynamics.

4. Results

Figure 2: Stock Prices versus Return Rates

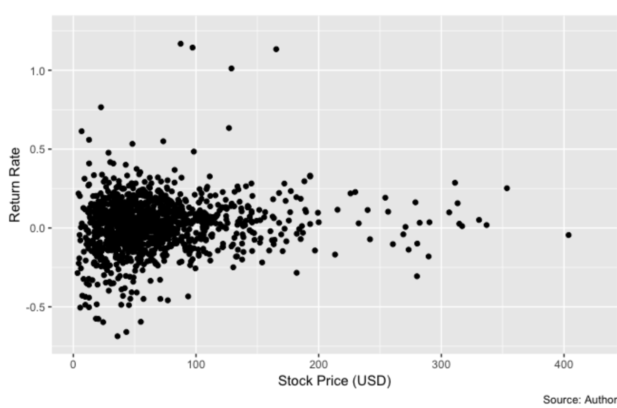
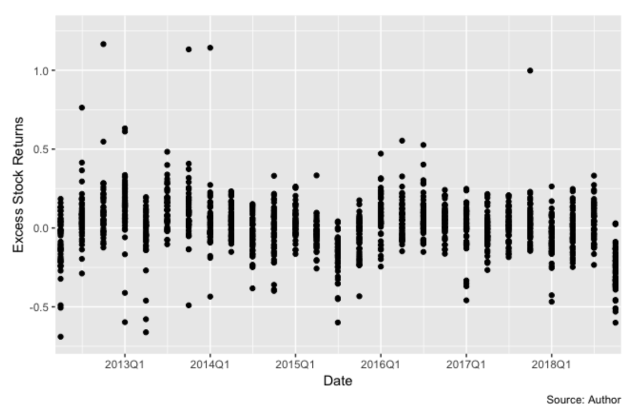


Figure 3: Excess Returns Price Dispersion



Note: Figure 2 illustrates the relation between stock prices and return rates over time. Stock prices vary between 3.242 and 422.652 USD. Figure 3 shows price dispersion for excess returns (48 quarterly observations for each individual point in time).

Table 1 provides summary statistics for the dependent and explanatory variables in the panel regression (8). The Shapiro-Wilk (SW) test rejects the null hypothesis of normality for all the variables.[3] Wah and Sim (2011) show that the SW test performs better for symmetric short-tailed and asymmetric distributions, and similar results are obtained from the Jarque-Bera and

[3] We obtain a p-value of less than 0.05 for all the model parameters. Although violation of the population normality assumption is not a major problem when the sample size has $n \geq 100$ observations, assessing the normality of the variables is a prerequisite to avoid faulty inference. Specifically, a normal distribution suggests the use of the mean instead of the median value, and vice versa when comparing between groups. For meaningful conclusions, we provide both the mean and the median in the summary statistics.

Table 1: Descriptives

	Panel A. Summary Statistics						Panel B. Correlation Matrix			
	Mean	Median	Max	Min	SD	SW	RM-RF	SMB	HML	Pr^D
R	0.018	0.023	2.250	-0.686	0.178	0.865				
RF	0.006	0.003	0.025	0.001	0.007	0.773				
RM	0.013	0.023	0.080	-0.130	0.046	0.877				
Pr^W	0.024	0.000	1.000	0.000	0.059	0.469				
R-RF	0.011	0.018	2.247	-0.689	0.179	0.866				
RM-RF	0.006	0.015	0.079	-0.155	0.049	0.864	1.000			
SMB	0.002	-0.012	0.117	-0.056	0.040	0.905	0.076	1.000		
HML	0.061	0.059	0.205	-0.054	0.060	0.968	-0.178	0.256	1.000	
Pr^D	0.000	-0.008	0.883	-0.116	0.053	0.691	0.000	0.000	0.000	1.000

Note: The table shows summary statistics (%) for 48 US entities listed on the NYSE between 2012Q1 and 2018Q4 (1296 observations). R is the stock return calculated as $(P_t/P_{t-1}) - 1$ and P the stock price obtained by dividing the asset market value by outstanding shares. RF indicates the risk-free return and $R-RF$ the average quarterly return in excess of the three-month US short-term interest rate. RM is the quarterly value-weighted return for the six portfolios from 2×3 sorts on size and B/M and $RM - RF$ is the excess market return. SMB is the difference between average returns on small and large portfolios with approximately the same weighted-average B/M. HML is the difference between high- and low-B/M portfolios having the same weighted average size, Pr^W is the individual probability of an asset downgrading and Pr^D is the difference between a stock's individual probability of downgrading and the mean probability of downgrading across stocks grouped by time and the 2×3 portfolio sorts on size and B/M. We use the SD to measure price volatility and risk. The SW test is more appropriate for samples having fewer than 2000 observations. Panel A shows summary statistics and Panel B reports correlations for each set of common risk factors.

D'Agostino tests for symmetric long-tailed distributions with sample sizes below 2000 observations. Stock returns with low standard deviation (SD) suggest low price dispersion and less volatility over time (Figure 2). HML incorporates higher risk (0.060) than the other factors. The portfolio produces a low range of excess returns (Figure 3), meaning that the average premium per unit of market- and size-related factors is small from an investment perspective. Note that in contrast, HML as a factor incorporating higher risk, generates a higher average premium. Note further that the median produces higher premia for $RM-RF$ than the mean due to a long tail of negative values. Conversely, a negative premium for SMB indicates a positive skew. The negative value suggests that, on average, small entities tend to achieve lower returns than large entities. HML stands for the difference between average quarterly returns on high- and low-B/M-portfolios with the same weighted average. The difference between the two components should be largely unaffected by the size-related factor, capturing instead the different return behaviors of high- and low-B/M firms (Fama and French, 1993).

Panel B indicates that the correlation between the size and B/M-related factors is relatively weak (0.256). A positive value of HML suggests that the value stocks with a high B/M ratio outperform the growth stocks with a low B/M ratio in the long run. For the rest of the risk components in Panel B, the correlations obtained are weak.

Table 2 indicates results on panel regressions that use the FF three-factor model (Panel A) augmented by Pr^D (Panel B) to explain excess returns. β_0 denotes the risk premia over the risk-free $R-RF$, which under the EMH are zero. Both specifications here yield positive intercepts β_0 and suggest that the portfolio overperforms its market benchmark. The estimated coefficient on $RM - RF$ indicates that the market return is over the risk-free rate. The positive slope points to a 1.5 percent increase in stock excess returns for a one-unit change in the market excess return. A positive $\hat{\beta}$ for SMB for the sample considered demonstrates tilting toward small factor exposures.

Table 2: Panel Regressions on Excess Returns

	β_0	RM-RF	SMB	HML	Pr^D	R^2	R^2_A	RSS
Panel A. Excluding Pr^D								
RE	0.025***	1.491***	0.573***	-0.407***		0.220	0.218	32.485
	(0.006)	(0.092)	(0.112)	(0.077)				
FGLS	0.023***	1.391***	0.559***	-0.366***		0.219		32.530
	(0.002)	(0.069)	(0.038)	(0.035)				
MG	0.028***	1.482***	0.562***	-0.406***		0.323		28.181
	(0.007)	(0.099)	(0.086)	(0.072)				
Panel B. Including Pr^D								
RE	0.025***	1.491***	0.573***	-0.407***	-0.300***	0.228	0.226	32.147
	(0.006)	(0.091)	(0.112)	(0.076)	(0.081)			
FGLS	0.023***	1.389***	0.547***	-0.350***	-0.259***	0.227		32.210
	(0.002)	(0.067)	(0.037)	(0.037)	(0.035)			
MG	0.031***	1.489***	0.578***	-0.423***	-0.404**	0.361		26.596
	(0.007)	(0.101)	(0.100)	(0.070)	(0.143)			
Pesaran CD: 0.000	Breusch-Godfrey LM: 0.000		Breusch-Pagan: 0.000					

Note: The table summarizes three- and four-factor regression results for stock excess returns. Both model versions are estimated using RE, FGLS and MG estimators. The Hausman test suggests the use of RE both excluding and including Pr. ***, **, and * denote statistical significance at 1%, 5%, and 10% level respectively. The standard errors are included in parentheses. The Pesaran CD test rejects the null hypothesis (H_0: no cross-sectional dependence) under OLS. The Breusch-Godfrey LM test shows evidence of serial correlation in the idiosyncratic error term (H_0: $e_{i,t}$ is serially uncorrelated) while the regressions fail the Breusch-Pagan test of heteroskedasticity (H_0: constant variance). We report the p-values for all test diagnostics. The dependent variable $R - RF$ is the average quarterly return in excess of the three-month US short-term interest rate. R the stock return calculated as $(P_t/P_{t-1}) - 1$, P the stock price obtained by dividing the asset market value by outstanding shares and RF the risk-free return. RM is the quarterly value-weighted return for the six portfolios from 2×3 sorts on size and B/M and $RM - RF$ is the excess market return. SMB is the difference between average returns on small and large portfolios with approximately the same weighted-average B/M. HML is the difference between high- and low-B/M portfolios having the same weighted average size and Pr^D is the difference between a stock's individual probability of downgrading and the mean probability of downgrading across stocks grouped by time and portfolio sorts on size and B/M. FGLS and MG do not report adjusted R^2 (R^2_A).

The portfolio return grows as mid-sized firms' excess returns increase compared to large firms' excess returns. Fama and French (1993) argue, however, that positive exposure to size-related risk reduces average excess returns on small and medium market-sized portfolios. A negative $\hat{\beta}$ for HML shows greater sensitivity to low-B/M stocks. Low-B/M equity firms earn lower risk premia and exhibit lower financial leverage and less earnings uncertainty than their high-B/M counterparts (Chen and Zhang, 1998). Note that the SMB and HML loading factors vary between considerably negative values for low size- or B/M-related portfolios to considerably positive values for large size- or B/M-related portfolios; see Table 1.

Using transition matrices to estimate credit migration risk, we provide robust empirical evidence to support a statistically significant negative downgrade risk premium in excess returns. Excess returns decrease while firms' individual probability of downgrading grows higher than the group's average probability (Griffin and Lemmon, 2002; Campbell et al., 2008; Avramov et al., 2009a). This is not the outcome one would expect if downgrade risk were systematic and shareholders sought a premium for it. In case of risk being nonsystematic, on the other hand, there should be no return differential due to credit risk. The negative risk premium reveals an anomaly in the cross-section of stock returns as investors appear to pay a premium for bearing credit risk.

If the market underreacts to downgrade risk, the stock prices of distressed firms are not discounted sufficiently, leading to low prior-year returns. Low returns continue over time, in turn generating a negative financial distress risk premium and continuation of prior return momentum (Agarwal and Taffler, 2008b). In a similar vein, Avramov et al. (2007) discover momentum amongst high credit-risk stocks and argue that the unanticipated deteriorated operating and financial performance of low-rated stocks after credit rating downgrades leads to subsequent stock price underperformance. The results are driven by the worst rated stocks comprising just 0.77% of the sample by market capitalization and 4.22% of the total number of firms. Although the authors argue that leverage is a better proxy for distress risk than credit ratings, Agarwal and Taffler (2008b) show that it is the market mispricing of underlying bankruptcy risk that drives momentum and suggest that credit risk and financial distress are indistinguishable.

The outcome suggests that distressed stocks earn lower returns than nondistressed stocks, as the market slowly realizes its error and thus slowly drives down distressed stock prices (Dichev, 2002; Vassalou and Xing, 2004; Campbell et al., 2008). High distress intensity implies that a firm gradually exhausts its capacity to issue low-risk debt. Firms with riskier cash flows exhibit lower cash-flow growth and a higher probability of default for a given level of debt, which in turn increases transaction costs. As a result, high-cost firms utilize less leverage (debt) to scale back their probabilities of financial distress (Hovakimian et al., 2001; Korajczyk and Levy, 2003; Faulkender and Petersen, 2006; Kayhan and Titman, 2007). Therefore, firms with higher real PDs achieve lower cash-flow risk and consequently lower stock returns in the long run (Ho et al., 2006; George and Hwang, 2010b). Note that the time span we examine reflects a transitional period for the stock market with volatile credit conditions and changes in the bankruptcy law that lead to negative surprises in the realized cash flows of high default-risk stocks. Furthermore, Garlappi et al. (2008) argue that equity-holders of distressed firms behave opportunistically and violate the absolute priority rule (APR), which in turn has a direct impact on equity risk. Another argument for the negative relationship could be that institutional preferences for safer stocks have significantly increased over time (Qing et al., 2019). In particular, Kovtunenko and Nathan (2003) find that institutions tend to avoid small stocks with low accounting profitability and highlight a shift in the overall institutional strategy towards mid- and large-cap US equities since 2001. Campbell et al. (2008) demonstrate that distressed stocks underperform more strongly when institutions exhibit low ownership share. Analyzing the credit risk puzzle, they show that the distress effect is stronger among small-cap stocks, that are highly illiquid, monitored by few analysts, and difficult to short sell. Due to market inefficiency, there is normally minimal awareness of how highly overpriced these stocks are, while short-selling constraints prevent arbitrageurs from quickly and completely exploiting mispricing opportunities.

The new credit risk factor captures the distress effect in mid- and large-cap entities, and suggests that the momentum anomaly can be exploited by investors even when it is not driven by small illiquid stocks (Lesmond et al., 2004). From an economic perspective, trading strategies that target long low-default risk and short high-default risk mid- and large-cap stocks during non-downgrade periods provide economically small payoffs. Adding Pr^D to the model does not substantially impact the regression coefficients due to the low correlation between the common risk factors. Moreover, the distress effect is robust across several estimation approaches. All factors, both in Panels A and B, are statistically significant. In conclusion, Pr^D exhibits additional pricing power explaining variations among average stock returns.

To test for endogeneity, we propose the Dumitrescu and Hurlin (2012) panel Granger non-

Table 3: Granger Noncausality Tests

	$K=1$			$K=2$		
	$\tilde{Z}_N^{Hnc}$	$\bar{Z}_{N,T}^{Hnc}$	$W_{N,T}^{Hnc}$	$\tilde{Z}_N^{Hnc}$	$\bar{Z}_{N,T}^{Hnc}$	$W_{N,T}^{Hnc}$
Panel A. $H_0 : i = \{RM - RF,\ SMB,\ HML,\ Pr\}$ does not Granger-cause $R - RF$						
RM-RF $\nRightarrow$ R-RF	0.159	0.649	1.133	1.448	2.561*	2.747
	(0.873)	(0.516)		(0.147)	(0.010)	
SMB $\nRightarrow$ R-RF	-1.882	-1.756	0.637	0.047	0.821	2.239
	(0.059)	(0.079)		(0.961)	(0.411)	
HML $\nRightarrow$ R-RF	-0.862	-0.555	0.885	-1.215	-0.748	1.781
	(0.388)	(0.578)		(0.224)	(0.454)	
$\mathrm{Pr}^D \nRightarrow$ R-RF	1.994*	2.812**	1.580	2.672**	4.082***	3.190
	(0.046)	(0.004)		(0.007)	(0.000)	
Panel B. $H_0 : R - RF$ does not Granger-cause $i = \{RM - RF,\ SMB,\ HML,\ Pr\}$						
R-RF $\nRightarrow$ RM-RF	-0.814	-0.497	0.897	-0.818	-0.255	1.925
	(0.415)	(0.618)		(0.413)	(0.798)	
R-RF $\nRightarrow$ SMB	2.154*	3.000**	1.618	1.517	2.646**	2.772
	(0.031)	(0.002)		(0.129)	(0.008)	
R-RF $\nRightarrow$ HML	2.796**	3.756***	1.775	0.792	1.746	2.509
	(0.005)	(0.000)		(0.427)	(0.080)	
R-RF $\nRightarrow$ Pr^D	0.621	1.193	1.246	0.619	1.531	2.446
	(0.534)	(0.232)		(0.535)	(0.125)	

Note: The table reports panel Granger noncausality tests by Dumitrescu and Hurlin (2012). The average Wald statistic $W_{N,T}^{Hnc}$, the asymptotic standardized statistic $\bar{Z}_{N,T}^{Hnc}$ (for large-T samples), the semi-asymptotic standardized statistic $\tilde{Z}_N^{Hnc}$ (for small values of T and N), and the associated p-values (in parentheses) are displayed. There is no p-value available for the $W_{N,T}^{Hnc}$ statistic. Given the null hypothesis, there is no causality among the variables of interest for all individuals in the panel (H_1: there is causality among the variables of interest for at least one individual in the panel). ***, **, and * denote statistical significance at 1%, 5%, and 10% level respectively. A statistically significant relationship implies rejection of H_0. $R - RF$ (dependent) is the average quarterly return in excess of the three-month US short-term interest rate. R is the stock return calculated as $(P_t/P_{t-1}) - 1$, P is the stock price obtained by dividing the asset market value by outstanding shares and RF is the risk-free return. RM is the quarterly value-weighted return for the six portfolios from 2×3 sorts on size and B/M and $RM - RF$ is the excess market return. SMB is the difference between average returns on small and large portfolios with approximately the same weighted-average B/M. HML is the difference between high- and low-B/M portfolios having the same weighted average size and Pr^D the difference between a stock's individual probability of being downgraded and the mean probability of downgrading across stocks grouped by time and portfolio sorts on size and B/M.

causality procedure. The method assumes independently and normally distributed residuals with finite heterogeneous variances and covariance-stationary variables. We utilize standardized statistics in Table 3 as computed by way of averaged Wald statistic. Under the null hypothesis, there is no causal relationship running from $i = \{RM - RF,\ SMB,\ HML,\ Pr^D\}$ to $R - RF$, and vice versa for all entities in the panel. Symmetrically, there is at least one and at most $N - 1$ noncausal interdependencies in the model. The tests are conducted using one and two optimum lags (K), respectively. The results indicate a unidirectional causal relationship running from downgrade risk to excess returns suggesting no threat of endogeneity due to simultaneity. Regarding the remainder of the common risk measures, most of the test statistics provide no evidence of causality, the lone exception being a reverse relationship in case of SMB and HML (Panel B).

Nevertheless, several plausible explanations and feasible implications for future research aim to clarify as to why we should be prudent when assessing the predictive power of the above diagnostic. First, the sample size is small, and the data set has not been segmented. While we classify all corporate entities into separate industries when calculating transition probabilities, we do not form separate portfolio strategies, thus skewing evidence of causality. Second, the presence of unidirectional causality may be sample-specific. In particular, transition probabilities are calculated using the total number of entities on the US stock market migrating from G to g at t. They may hence reflect the general tendency of the market rather than the performance of the stock itself. Consequently, establishing a robust cause-effect relationship between the two factors becomes more challenging.

Table 4: Out-of-sample Model Validation

	Panel A. Overall Model Fit				Panel B. Forecast Performance			
Model	$H = 1$	$H = 2$	$H = 3$	$H = 4$	$H = 1$	$H = 2$	$H = 3$	$H = 4$
Excluding Pr								
RE	0.14221	0.14221	0.14220	0.14222	0.11864	0.12093	0.11930	0.12124
FGLS	0.14227	0.14226	0.14221	0.14220	0.12322	0.12298	0.12043	0.12187
MG	0.14223	0.14223	0.14225	0.14225	0.11909	0.12112	0.11961	0.12138
Including Pr								
RE	0.14158	0.14157	0.14157	0.14159	0.12068	0.12118	0.11949	0.12051
FGLS	0.14160	0.14160	0.14157	0.14155	0.12481	0.12321	0.12072	0.12128
MG	0.14207	0.14212	0.14220	0.14222	0.12245	0.12198	0.12045	0.12196

Note: The table summarizes RMSEs for each model and horizon. The reported statistics are averages based on the RMSEs obtained across individual units. First, we estimate each model running recursive regressions over 2012Q1–T, where T =2017Q4, ..., 2018Q3. Second, we use the obtained coefficients to calculate H-step ahead forecasts for each individual unit, where $H = 1, ..., 4$ quarterly forecasting horizons. For the forecast period from 2018Q1 onwards, we utilize actual values for all independent variables. The final ratio reported in the table, is the average RMSE calculated recursively over 48 stocks, 6 model specifications and four different forecasting horizons. Panel A shows RMSEs calculated including the full sample period, and Panel B reports RMSEs calculated including only the forecast period.

To assess the out-of-sample model performance, we forecast the near-term outlook of excess returns. We set a four-quarter-ahead simulated out-of-sample root mean square error (RMSE) as the validation criterion for the competing models (Table 4). Specifically, we estimate both models using data from 2012Q1 to 2017Q4 and generate four-quarter ahead forecasts ($H = 4$). We then add an additional quarter to the actual data set (2018Q1), and again generate forecasts for the remaining quarters (2018Q2-2018Q4). We employ this recursive method for a total of four times. Finally, we calculate the out-of-sample RMSE averaging 48 individual forecast errors for $H = 1$, 96 for $H = 2$, 144 for $H = 3$, and 192 for $H = 4$ horizons ahead (Panel B). Note that Panel A summarizes RMSEs calculated for the full sample period (2012Q1-2018Q4) using four different regression coefficients. The results suggest that the augmented model outperforms the FF three-factor model across all forecast horizons and model specifications with regard to the overall fit. In contrast, the FF three-factor model performs better in the short term than the augmented version when exclusively assessing forecast performance (Panel B). Note, however, that as the forecast horizon increases, the augmented model outperforms its benchmark, thus demonstrating less uncertainty in the long term.

5. Concluding Remarks

Several studies calculate distress risk measures using both accounting and market-based methods (Agarwal and Taffler, 2008a; Campbell et al., 2008; Gomes and Schmid, 2010; Da and Pengjie, 2010; Avramov et al., 2013; Charitou et al., 2013). This paper extends the FF three-factor model to investigate risk exposures arising from credit rating transition probabilities and provides evidence for the distress anomaly among mid- and large-cap stocks. While we classify all corporate entities into separate industries when calculating transition probabilities, we do not form separate portfolio strategies given the size of the sample. Instead, we focus on the model's performance per se and the link between excess returns and downgrade risk in terms of credit transition dynamics.

Using transition matrices to estimate credit migration risk, we provide robust empirical evidence to support a statistically significant negative downgrade risk premium in excess returns. Stocks at higher risk of downgrading tend to deliver lower excess returns (Campbell et al., 2008; Avramov et al., 2009b; Da and Pengjie, 2010; Garlappi and Yan, 2011). The new risk factor exhibits additional pricing power in explaining variations among excess returns, even when accounting for firm size and B/M ratio. The performance of the model remains robust across several estimation methods. The Dumitrescu and Hurlin (2012) panel Granger causality test provides evidence to support a unidirectional causality running from excess stock returns to downgrade risk. However, there is evidence of reverse causality in the case of SMB and HML factors.

From an economic perspective, the negative risk premium reveals an anomaly in the cross-section of stock returns, suggesting that investors underreact to the risk of failure, and this translates to subsequent stock price underperformance. The credit risk effect indicates that trading strategies targeting long low-default risk and short high-default risk mid- and large-cap stocks during non-downgrade periods provide economically small payoffs. A potential avenue for future research might be an investigation of whether increasing the sample size and exploring portfolio strategies based on the new factor yields additional insights into to asset pricing anomalies.

Acknowledgements

We gratefully acknowledge financial support from the Charles University PRIMUS program (project PRIMUS/19/HUM/17). This work has been supported by Charles University Research Centre program No. UNCE/HUM/035. We are also thankful for the feedback and comments by the faculty and students at the Charles University Institute of Economic Studies, and the participants of the 3rd International Conference on Econometrics and Statistics in Taichung (2019) and the 13th International Conference on Computational and Financial Econometrics in London (2019).

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