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Abstract
Daniel and Titman (DT) (1997) disclaim the Fama-French three factor model in favor of a firm characteristics based model to explain stock returns. Davis, Fama, and French (2000) find this characteristics-based model outperforms their model only for the 20.5 year time period from July 1973-December 1993, but the three factor model is robust for the 68-year period from 1929-1997. We find the DT period represents a unique macroeconomic environment in that significant interaction effects exist between the default (and term) risk premia innovations and returns. Incorporating these effects into a traditional three-factor model help explain the 1973-1993 "characteristics model puzzle," providing insight into market returns for portfolio managers during economic environments comparable to the DT period.

Keywords: Three factor model, Charateristics based model, DEF, TERM, SMB, HML
JEL Classification: C3, E4, E5, G3, N1

I. Introduction

Many have attempted to explain sources of risk that asset prices account for in generating equity returns, perhaps beginning with the Fama-MacBeth (1973) tests of the Sharpe (1964) and Lintner (1965) capital asset pricing model (CAPM). Arguably the most notable model that has augmented the market factor CAPM includes the Fama and French (FF) three factor model. This model includes the factors related to size, book-to-market (B/M), and the market premium from the traditional CAPM model. To bolster their empirical results with theory, FF reason these factors collectively price the risk of financial distress. The tenuous theoretical strength of these factors, however, has led multiple studies to find other factors that either outperform or meet the standard established by the three factor FF model. This paper enhances the literature by further validating that when the risk climate is elevated (i.e., default premium changes are in the highest decile), it's prudent to incorporate changes to the macroeconomic environment when explaining security returns.

II. Literature Review

Consistent with the Merton's (1973) ICAPM approach, Petkova (2006) finds a model that includes innovations in predictive dividend yields explains cross-sectional returns better than FF. Meanwhile, Vassalou (2003) finds a model, which includes a factor representing GDP growth news along with the market factor that subsumes much of the FF factors' cross-sectional explanatory power. A study by Chung, Johnson, and Schill (2006) contends that including higher order comments of order 3-10 nullifies the FF three factors' explanatory power. Although rebutted strongly by Davis, Fama, and French (FFD) (2000), Daniel and Titman (DT) (1997) provide additional insight with their conclusion that pricing assets using firm characteristics provides a better model than the FF factors. FFD (2000) readily acknowledge DT's characteristic model results, at least for their in-sample period of 1973-1993. However, they maintain the three-factor model's superiority over the 68-year time period from 1929-1997. This unique result for the period 1973-1993 motivates this study and provides a potentially useful consideration for portfolio management.

Investigating further the divergence between the DT and FF results, one gains insight into the value of implementing conditional factors to explain cross-sectional asset returns, akin to Ferson and Harvey (1999). While Ferson and Harvey (1999) use four lagged conditional variables to create their time-varying betas, we focus on contemporaneous instruments with a slight difference in our definitions of the selected macroeconomic factors; term rate risk (TERM) and default risk (DEF) premia. Additionally, we address both time-varying betas while also generating constant alphas in our series of two-pass regression models.[1] Ultimately we conclude the validity of DT's results hinge on the unique interrelationship between macroeconomic factors and FF's "distress" factors during the DT period of study. As Chan, Karceski, and Lakonishok (1998) find, of all macroeconomic factors tested, only TERM and DEF perform with merit in exhibiting covariance with asset returns. Further, Hahn and Lee (2006) describe how these two macroeconomic variables represent business cycle fluctuations. They find innovations in TERM and DEF obviate the Fama and French-developed size factor (SMB) and book equity-to-market equity factor (HML) in a model explaining the size and value effects. Therefore, Hahn and Lee (2006) argue SMB and HML are essentially proxies for credit market conditions that are more aptly represented by DEF and TERM. This explanation, coupled with the results in this paper, enhances the merit of a modified FF three-factor model when macroeconomic environments exist akin to those during the DT period.

The remainder of the paper is organized as follows. Section II provides an overview of the data used in this study. Section III outlines the models incorporated in the paper and provides an analysis of the results. In Section IV we present and evaluate the differences for HML loading during the DT period. The paper ends with a discussion and conclusion.

III. Data

The returns for the 25 US equity portfolios, created and maintained by Ken French on his website[2], represent the intersection of stocks independently sorted into quintiles by size—or market capitalization—and book equity-to-market equity ratio (B/M). The equities are sorted annually at the end of every June to obviate any end of year or January effects, placed into their respective quintiles, and evaluated as members of this quintile (e.g., small size/low B/M, small size/high B/M, etc.) for the subsequent year. Equities belong to NYSE, NASDAQ, and AMEX. For sorting into quintiles, firm characteristic information comes from COMPUSTAT, and return information comes from the Center for Research in Security Prices (CRSP). FF (1993) provides additional details on this sorting procedure.

We generate the default and maturity risk premia—DEF and TERM, respectively—by differencing the Moody's seasoned Baa corporate bond yield[3] and the one-month Treasury[4] and the difference between the 10-year Treasury constant maturity rate and the one-month Treasury. Hahn and Lee (2006) cogently argue that these risk premia proxy for credit market risk and

[1] Fama and MacBeth (1973) provide procedural details
[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[3] Federal Reserve Economic Data (FRED) database: http://research.stlouisfed.org/fred2/.
[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (pulled from CRSP)

interest rate risk, respectively. Thus abnormal changes to these yield spread measures depict changes in market predictions about the future of credit markets and interest rates. Accordingly, these yield spread variables appear to proxy for credit market risk and interest rate risk. In another work, using a variable-by-variable method to select best-performing potential factor variables, Chan, Karceski, and Lakonishok (1998) find that of the macroeconomic factors they test (e.g., growth rate of monthly industrial production, return on long-term government bonds or the real interest rate, slope of the yield curve, change in monthly expected inflation, and unexpected inflation) only DEF and TERM perform well in capturing systematic return covariation, even in the out-of-sample Japanese and UK markets. Additionally, others such as Campbell (1996), Keim and Stambaugh (1986), and FF (1989), rationalize that state variable proxies should stem from their ability to forecast asset returns and that these default and term spread variables do indeed forecast aggregate stock market returns.

While DT (1997) initially base their hypothesis on data from July 1963-December 1993, the essence of their results stem from the 20.5 years between July 1973 and December 1993. To reach their conclusions about the superiority of a characteristics-based model over the FF three factor model, data limitations from July 1963-June 1973 force them to omit this decade of returns in their comparison of the models.

In contrast, FFD (2000) reach conclusions using the 68-year period from 1929-1996. Because our data on the 10-year Treasury, which we use to calculate TERM, begins in April 1953, our initial analysis spans the 55-year period from April 1953-August 2008. While the period is shorter than FFD (2000), causing a marginal decrease in statistical power, it is still over 2.5 times the amount of data used in the DT study, which enhances our relative statistical power. Additionally, besides capturing the 20-year DT period, this time span captures 20 years (15 years) of pre-DT (post-DT) data, with the pre-DT and post-DT mean excess returns aligning closely with those of the FFD (2000) period. Table 1 shows the summary statistics for this study. While not a perfect replication of returns from DT (1997) or FFD (2000), these returns appear virtually identical in trend (showing the size and value premia) and similar in value to both DT Table 1 (see "All Months") and FFD Table II (see "Ex Ret" column for the 7/63-6/97 period). For completeness, we include the DT and FFD tables in Appendix 1.

IV. Models and Analysis

DT (1997) focuses on the value premium that portfolios of stock returns consistently exhibit. That is, firms with higher book equity-to-market equity ratios (B/M) exhibit higher excess, or risk-adjusted, returns than firms with lower B/M. FF capture the loading for this risk using a B/M factor they call HML, which is the per-period return premium for a zero investment portfolio consisting of a simultaneous long (short) position in high (low) B/M stocks. Further, FFD (2000) highlight four existing explanations for this phenomenon: (1) a chance result unlikely observed out of sample (Black, 1993, and MacKinlay, 1995), (2) compensation for risk in a multifactor model such as Merton's (1973) ICAPM or Ross' (1976) arbitrage pricing theory (APT), (3) investor overreaction to firm performance a la Lakonishok, Shleifer, and Vishny (1994), or (4) it results from the value characteristic instead of risk as modeled by DT (1997). Again, it is this final explanation that is the core of this study. Based on its outperformance of the FF three factor model for the 20-year period late last century, we specifically explore reasons for the superiority of the DT model, believing it portends lessons for equity returns should similar circumstances occur in the future. Going forward, like Chan, Karceski, and Lakonishok (1998), we initially focus on the factor loadings in this paper.

An initial inquiry into the apparent divergence of the DT and FF models forces one to consider whether one or more conditional factors existed during the DT period that do not hold the same influence in the non-DT period. Noting the unique energy crisis, economic stagflation, and savings and loan crisis, which occurred during the DT period, one is quickly led to consider macroeconomic factors and their influence on asset returns. Based on the Chen, Roll, and Ross (1986) precedent, FF (1993) used versions of the default risk premium (DEF) and maturity risk premium (TERM) factors to price bond returns.

Conditioning the FF factors on these two macroeconomic factors, it's possible to develop joint probability density functions (pdfs) by sorting firms into the FF SMB and HML quintiles and then independently into DEF and TERM quintiles. The resulting histogram provides a sample pdf. Figure 1 juxtaposes various combinations of the DT period and entire sample period joint pdfs. A visual analysis indicates the interrelationship between SMB and HML with DEF and TERM differs between these periods of interest, indicating a possible explanation for the difference in the DT characteristics and FF three factor models. For instance, the first set of plots (i.e., DT Period) shows in low DEF (when DEF=1) months within the DT period SMB is skewed right compared to a more normally-distributed SMB distribution for the entire period (i.e., Entire Period). While multiple other differences are apparent, perhaps the most glaring occur in the last joint pdfs shown, where the DT period shows large numbers of stocks in the low TERM-low HML (1,1), low TERM-high HML (1,5), and high TERM-high HML (5,5) joint quintiles. Alternatively, for the entire period, these extreme quintiles are relatively lower than their non-extreme counterparts. Despite the initial insights these plots provide, Figure 1 is merely intended to offer a visually intuitive representation of the differences in data between the DT and entire sample regimes. Clearly we can draw no statistical conclusions based on such a cursory visual analysis.

However, continuing the initial graphical analysis of the different macroeconomic environment of the DT period, it's constructive to investigate the time series of both the FF factors and the macroeconomic factors. Figure 2 shows the time series of HML and SMB, respectively, plotted against both DEF and TERM. As one would expect, both HML and SMB appear relatively stationary despite the extreme volatility in the year 2000, while the DEF and TERM values display a hump-shaped pattern with the apex virtually bisecting the DT period. As suspected, these factors are non-stationary. The non-DT DEF and TERM time trends, while increasing (decreasing) in the pre-DT (post-DT) period, appear almost as mirror images outside the DT period despite the opposing trends. A T-test of differences indicates both DEF and TERM have statistically higher (lower) first (second) moments in the post-DT period compared to the pre-DT period, which isn't a surprising result given the post-DT time period has approximately 2/3 of the data as the pre-DT period.

It becomes apparent that DEF and TERM exhibit very similar patterns and are in fact highly correlated during this time period with a correlation exceeding 0.99. As a result, using both series in our models would increase the likelihood of multicollinearity issues. Since DEF is available for a much longer time period, we focus on its use going forward, relegating TERM to side comments. Doing so expands our overall time series to over 82 years, from July 1926-August 2008. Figure 3 displays this data, indicating a similar pattern as before for SMB and HML, and verifying that the DT period indeed represents an anomalous macroeconomic timeframe given the history of this recorded financial data. Absolute DEF levels during the DT period are almost universally higher than the other clear peak that occurred during the 1930s.

Given this apparently unique macroeconomic timeframe within which DT determine asset returns, we hypothesize that models accounting for this difference explain returns differently than the standard FF three factor model. We proceed by establishing a baseline for the unconditional factor loading differences between the DT and non-DT periods and then incorporate the macroeconomic proxies as factors to assess both the independent and interactive effects of including this macroeconomic information.

Determining the DT period difference for HML loading

Since DT focus initially on the value premium, which is the fact that higher B/M portfolios exhibit higher returns, our primary focus is likewise on HML. We include SMB results for completeness. The first assessment we make is that the HML factor loadings systematically differ between the DT and non-DT periods. SMB differs too, but not as systematically. Knowing FFD (2000) finds the 3-factor model is robust, any systematic loading differences begin to help us explain DT's unique results. To establish the variation in loading between the DT and non-DT periods, we estimate the following model, which is akin to the Fama-MacBeth (1973) first-pass:

$$R_{i,t} - R_F = \beta_0 + \beta_{i,HML}HML + \beta_{i,HML(DT)}HML \cdot DT + \beta_{i,SMB}SMB + \beta_{i,SMB(DT)}SMB \cdot DT + \beta_{i,M}(R_M - R_F) + \varepsilon_t \quad (1)$$

where $R_{i,t}$ is the return on FF portfolio i (i=1,…25), R_F is the risk-free rate (1-month Treasury bill), and $\beta_{i,j(k)}$ is the comovement of FF portfolio i with factor j (j=HML or SMB), R_M is the return of the market portfolio, and DT is a binary term equal to one during the DT time period and zero in the non-DT time period.

As with the three factor model, the non-DT HML loadings $\beta_{i,HML}$ and $\beta_{i,SMB}$ are all highly significant.[5] The results in Table 2 show the HML factor loadings in the DT period, $\beta_{i,HML(DT)}$. They are lower for 21 of 25 FF portfolios, controlling for the SMB and market factors, and the signs on the statistically insignificant coefficients are still negative. Notably, when HML loadings remain statistically constant between the DT and non-DT period, it's primarily for the low B/M firms (3 of the 4 cases occur here). Additionally, consistent with FFD (2000) trends, low B/M firms are the only ones with universally negative loadings on HML (i.e., negative coefficients in this column for both periods), and there exists a positive monotonic relationship between B/M and loading within each size quintile. Thus even in an environment with relatively higher default and term risk premia (the DT period), or what Hahn and Lee (2006) call higher credit-market risk and interest-rate risk environments, low B/M (i.e., growth) firms load equivalently on the HML factor as they do in environments that are less risky with respect to these macroeconomic factors. Meanwhile, essentially all other B/M portfolios load lower on HML during the macroeconomically riskier DT period than the less-risky non-DT period.

[5] These results are untabulated but are available upon request.

Important to note is that between the DT and non-DT periods the excess overall market returns are statistically indifferent in mean return (0.49% vs. 0.63%) and similar in standard deviation (4.77% vs. 5.41%). Since the 25 portfolios compose the market analyzed, the difference in the HML loadings between the two periods does not appear to simply result from wildly-fluctuating returns across this period.

We perform the same analysis as above with SMB and obtain the results in Table 3. Not surprisingly, based on the FFD (2000) discussion surrounding the relatively higher HML values, the SMB results exhibit much weaker patterns. While there is a significant difference in loading for the majority of portfolios in the DT period (14 of 25 cases), the loadings are roughly one-half greater than and one-half less than the non-DT period, leading to no universal conclusions. The only real apparent trends are the lack of difference in SMB loading between the DT and non-DT periods for the higher B/M (i.e., value) firms, and the statistical decreases in SMB loadings are primarily in the small-low corner. Thus for the DT period, value firms generally tend to load equivalently on SMB despite the credit market or interest rate risk environment, and growth firms tend to load lower on SMB relative to the balance of the 1926-2008 time period.

Overall, from this model we see that the FF 25 portfolios systematically load lower on HML during the DT period. And when statistically significant, these marginal changes going from the DT to non-DT period are non-trivial in magnitude, ranging from 16% to a more frequent 30-90% decrease (increase) for the vast majority of (low B/M) portfolios. High B/M portfolios rank among the lowest in loading percentage decrease. Thus when DT (1997) prices this HML loading in their sample period, the sensitivity is artificially low compared to the FFD (2000) loading for the longer time period.

Scaling FF by DEF (and TERM) inside and outside of the DT period

While we abstain from investigating directly the DT (1997) "conjecture that factor loadings measured with respect to the various macro factors used by [multiple authors] will also fail to explain stock returns once characteristics are taken into account," we look at conditioned factors next. Specifically, given the clearly unique macroeconomic environment during the DT period as exhibited by Figure 2, this model involves the use of these variables as scaling factors akin to Ferson and Harvey (1999). Since DEF and TERM are so closely correlated ($\rho = 0.99$), we condition on DEF due to greater time series data availability. Again, we use the following F-M (1973) first-pass model, where all variables are previously defined:

$$R_{i,t} - R_F = \beta_0 + \beta_{i,HML} HML + \beta_{i,HMLDEF} HML \cdot DEF + \beta_{i,SMB} SMB + \beta_{i,SMBDEF} SMB \cdot DEF + \beta_{i,M}(R_M - R_F) + \varepsilon_t \quad (2)$$

Table 4 presents the scaled coefficient results for the DT period, non-DT period, and the difference between the two periods accounting for the statistically-zero parameter values. Note for the first two panels that shaded cells indicate the coefficient is statistically significant using a 90% confidence level; for the last panel shading indicates a non-zero difference.

These results show using DEF as a conditional factor generates no overwhelming evidence of explanatory power in the DT period. The parameters for the non-scaled factors are significant in

22 of 25 and 17 of 25 cases for HML and SMB, respectively. If anything, it appears higher default spreads lead to lower SMB (and generally HML) loadings for lower B/M firms (i.e., significant interactive coefficients tend to cluster in the first two columns of each table and all but one sign is negative). One might also make a weak case that conditioning on DEF only affects the extreme size portfolios—both small and large—and again in a negative way (i.e., significant coefficients tend to occur across the first and last rows with all but one signed negative).

Alternatively, scaling HML and SMB by DEF for the non-DT period provides the second portion of Table 4. These results contrast the power of conditioning on DEF during the non-DT period versus the DT period. As a baseline, the non-scaled HML and SMB loadings are significant in 18 and 22 cases, respectively. Also, overall, the conditioned loadings are significant for a greater proportion of portfolios during this period. For HML, the coefficients are significant over 80% of the time (21 of 25 cases) for the non-DT period versus only 33% of the time (8 of 25) for the DT period. Particularly noteworthy is that for HML the significant time-varying loadings are generally positive for the preponderance of the cases (16) in the non-DT period, which means a higher default risk premium increases the HML loading, generally pushing it toward zero since the accompanying non-time-varying loadings are generally negative for these time-varying loadings. Additionally, when accounting for the statistically insignificant loadings, the time-varying portion of the loading is lower for the DT period than the non-DT period for 14 of 25 portfolios.

This result supports the earlier basic model (Table 2) where the HML loadings in the DT period were lower than the non-DT period for over 70% of the portfolios (18 of 25 cases). The inclusion of DEF-scaled loadings generally increases the overall HML loading, and in a magnified way compared to models that don't include such a time-varying component.

As for SMB conditioned by DEF, no pervasive trends materialize. The statistical significance of the loadings isn't proportionally greater in either case, nor does there exist a common direction. Nonetheless, similar to Ferson and Harvey (1999), these results indicate merit in permitting a time-varying beta based on changes in the default premia.[6]

Model Effects using Second-Pass Regressions

Since time-series returns are sensitive to DEF on its own and as a conditioning variable for the FF HML and SMB factors, it has merit as a factor that represents the unique macroeconomic environment during the DT period. We now turn to its effectiveness as a priced source of risk. In particular, given its noteworthy behavior during the DT period of study, can it explain the gap between the DT "characteristics" results for this period and the FFD results for the more expansive time period? We use the Fama-MacBeth (1973) second-pass regression models to generate our results.

Specifically, we evaluate three models during the DT (July 1973-December 1993), non-DT (July 1926-June 1973 and January 1994-August 2008), and whole (July 1926-August 2008) periods. These models include the (a) FF 3 factor model, to establish a baseline, (b) a model that

[6] Note we perform a similar analysis for TERM with similar results (for a shorter time period); we've included these results in Appendix 2.

conditions FF factors on DEF, and (c) a four factor model (similar to Elton, Gruber, and Blake, 1995) that augments the FF 3 factor model with DEF. Having established time series based betas for each factor as described earlier, below are the second-pass regression models we use to determine whether each source of risk is priced:

$$(a) \quad \overline{R_\iota - R_f} = \lambda_0 + \lambda_{HML}\beta_{i,HML} + \lambda_{SMB}\beta_{i,SMB} + \lambda_{MKT}\beta_{i,MKT} + \varepsilon_t \qquad (3)$$

$$(b) \quad \overline{R_\iota - R_f} = \lambda_0 + \lambda_{HML}\overline{\beta_{\iota,HML}} + \lambda_{SMB}\overline{\beta_{\iota,SMB}} + \lambda_{MKT}\overline{\beta_{\iota,MKT}} + \varepsilon_t \qquad (4)$$

where $\overline{\beta_{\iota,HML}}$ is the mean of the time-varying HML loading over the respective time period; the same process generates the mean time-varying SMB and MKT loadings

$$(c) \quad \overline{R_\iota - R_f} = \lambda_0 + \lambda_{HML}\beta_{i,HML} + \lambda_{SMB}\beta_{i,SMB} + \lambda_{MKT}\beta_{i,MKT} + \lambda_{DEF}\beta_{i,DEF} + \varepsilon_t \qquad (5)$$

In each model, $\overline{R_\iota - R_f}$ is the mean return for portfolio i, where I represents one of the 25 FF portfolios. The factor loading for each portfolio is generated from a time-series regression over the respective time period.

Ideally, since we've subtracted the risk-free rate to generate excess returns, if the factors in the model prices the returns precisely, then the intercept of each regression, λ_0, will equal zero. The loadings on HML and SMB vary in sign per the original three factor model. We expect a positive (or at minimum, zero) coefficient for the market factor loading since we intuitively expect a positive (not significant) relationship between the market beta and return. This "ideal" pattern for the parameter estimates is at the top of Table 5.

Table 5 shows the results from second-pass regressions (3), (4), and (5) for the whole period, DT period, and non-DT period. Interestingly, these results indicate the FF 3 factor model (a) doesn't completely price returns over the whole period due to the non-zero residual mean, and fails intuitively due to the sign on the price of market risk.[7] However, it performs as expected during the DT period, and the high adjusted R-squared value is glaring during the DT period. Thus despite the DT characteristics argument during their period of study, the FF 3 factor model stands out using the Fama-MacBeth two-pass testing method.

Unfortunately the conditional 3 factor model (4) fails in all three different time periods. SMB isn't priced in any of the time periods, which causes concern, and the low R-squared values indicate these conditioned factors aren't explaining a preponderance of the cross-sectional return variation. Finally, the non-zero constant makes it apparent these conditioned factors fail to completely price returns in the cross section.

That said, the four-factor model also performs as expected during the DT period, particularly in terms of the risk prices. Default risk is priced very high during this period, with SMB and HML at more conventional levels and the combination of these three subsuming the effects of market risk. These loadings do a fine job of explaining returns from the standpoint of the almost identically zero constant, although the adjusted R-squared is blatantly inferior to the FF three factor model.

[7] This finding is not unique to this study. See, for instance, Hahn and Lee (2006) and Fama and French (1992), who also find a negatively-sloped market beta.

The major concern with conditioning upon DEF is that it has a unit root. Thus we can create a more stationary and therefore statistically acceptable process by creating a one-period difference in default spread, which we call ΔDEF.

Recognizing DEF is among its highest levels during the DT period from Figure 2, we can also test whether the highest values of ΔDEF occur contemporaneously. Figure 4 maps DEF against the binary ΔDEF value where ΔDEF =1 when it's in the top decile, which translates to values greater than 0.21%. The overlap between the DT period and these high values of ΔDEF is apparent, as 39 of the 99 top decile months of ΔDEF occur in the DT period. Conveniently, ΔDEF also appears to pick up the other clear DEF "peak" in the early 1930s. As a result, we have a stationary variable with a threshold value at the 90th percentile that appears to generalize well the DT period and its peers.

Without belaboring the various model permutations possible given this information, we ultimately find conditioning SMB and HML on ΔDEF provides a model that provides insight into what occurs during the DT period. The first- and second-pass model regressions are shown below:

$$R_{i,t} - R_F = \beta_0 + \beta_{i,HML}HML + \beta_{i,HML(DT)}HML \cdot \Delta DEF + \beta_{i,SMB}SMB + \beta_{i,SMB(DT)}SMB \cdot \Delta DEF + \beta_{i,M}(R_M - R_F) + \varepsilon_t \quad (6)$$

$$\overline{R_\iota - R_f} = \lambda_0 + \lambda_{HML}\overline{\beta_{\iota,HML}} + \lambda_{SMB}\overline{\beta_{\iota,SMB}} + \lambda_{MKT}\beta_{i,MKT} + \varepsilon_t \quad (7)$$

where $\overline{\beta_{\iota,HML}}$ is the mean of the time-varying HML loading over the respective time period; the same process generates the mean time-varying SMB and MKT loadings

A summary of second-pass regression parameters follows in Table 6. We find that this general model prices excess returns using HML and SMB factors conditioned upon the one-period innovations in the default premium. The intercept is statistically insignificant, and even though the price of market risk is negative in sign, it's also statistically zero. The R-squared above 0.6 is also encouraging. We are also encouraged that this general model capturing high default risk premia innovations also works well during the specific DT period in question given the parameter significance and comparable R-squared values. Additionally, the model becomes questionable during the whole period, lending credence to the idea that interactive effects play a role generally when a macroeconomic factor like DEF experiences high innovations and specifically during the DT study period. Perhaps most importantly, a comparison between the scaled model and the FF three factor model (Table 6, Panel B) demonstrates the better relative performance of the scaled model during those periods where ΔDEF is at its highest decile. In descriptive terms, when DEF changes are among their highest values (i.e., in its highest decile), it's important to account for the changes in the macroeconomic environment if one wants to use the FF 3 factor model to explain security returns. Alternatively, firm characteristics better explain returns than the 3 factors during these types of extremely high credit market risk macroeconomic environments.

V. Conclusion

Unfortunately, despite the virtually indisputable explanatory power of the FF three factor model, a conclusive explanation for what exact risk(s) these factors capture remains elusive in the area of modern finance; Daniel and Titman (DT) (1997) do not make the solution any easier. As Davis, Fama, and French (2000) conclude, it appears the DT characteristics model for explaining equity returns works better than the FF three factor model due to the unique macroeconomic environment during the 20-year DT sample period. The default premium is uncharacteristically high for the duration of the 1973-1993 DT study period and accompanies a host of seminal economic events in US history such as stagflation and the savings and loan crisis. Additionally, not only are the absolute default premia values high during the DT period, so are its innovations. As a consequence, HML loadings systematically differ between the two periods and engender conflicting conclusions about the FF three factor model's robustness. SMB loadings also appear to differ, but in a less systematic sense.

Conditioning these two FF factors by innovations in the macroeconomic factor called the default premium (DEF), it's possible to explain the returns of the specific DT period using the Fama-MacBeth (1973) two-pass method. Perhaps more valuable, however, is the realization that the DT period is a special case of the more general periods where positive default premium innovations are in the upper tail, or top decile of its distribution. The conditioned factor model applies well during such periods and thus helps reconcile the diverging conclusions reached by DT and FFD.

While the FF three factor model has arguably represented one of the main standards for explaining stock returns in typical macroeconomic environments, when it comes to the extreme macroeconomic events, it appears asset return models could benefit by incorporating information that captures macroeconomic extremes such as the default and term spreads. Since these macroeconomic factors can be harbingers of potential black swan events, it may be instructive to consider their utilization when seeking positive alpha assets to include in portfolios. As we have learned since 2008, macroeconomic factors such as DEF and TERM can provide insight when forecasting seemingly anomalous events such as the financial crisis (Bredthauer and Geppert, 2013), which highlights the case that seemingly anomalous economic conditions akin to the DT period may not be so rare after all. Ultimately, portfolio managers could benefit from these findings by incorporating DEF and TERM when seeking positive alpha assets during economic conditions similar to the DT period.

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Figure 1

Figure 1 juxtaposes various combinations of the DT period and entire sample period joint probability density functions (pdfs). Constructing the joint pdfs first requires generating four common risk "factors": SMB, HML, DEF, and TERM for each month of the sample. The first column, "DT Period," shows the period July 1973 to December 1993; the second column, "Entire Period," shows April 1953 to August 2008. Within these periods the monthly factor values are sorted into quintiles. The quintile combinations are then put into their respective bins, creating the joint pdf. For instance, a low DEF value and high SMB value is over the DT Period is in bin (1,5), which is the furthest right column in the upper left pdf. Subsequent pdfs show various combinations of factors across both the DT and Entire time periods.

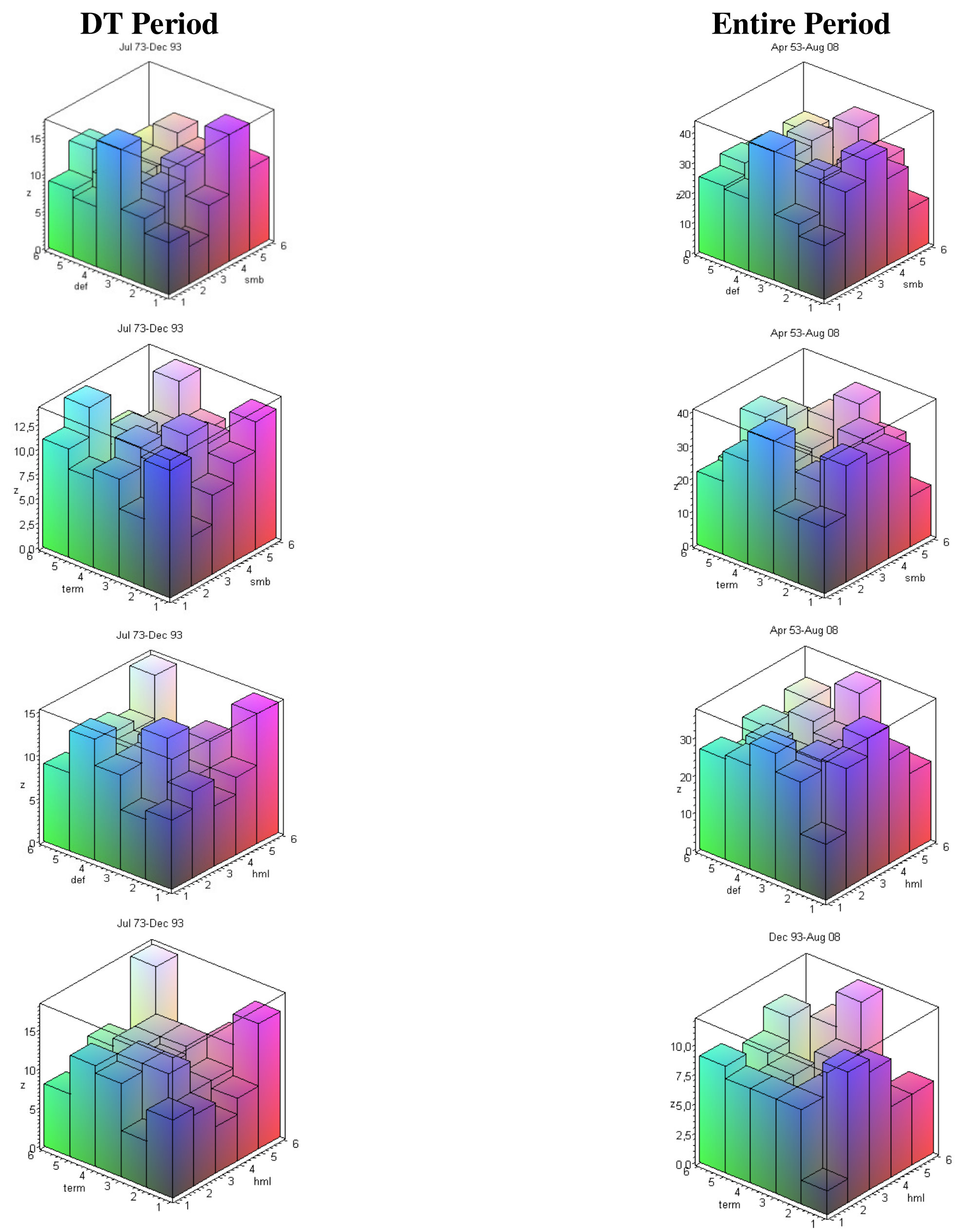

Figure 2

HML, SMB, DEF, and TERM from April 1953-August 2008

Figure 2 shows the time series of HML and SMB, respectively, plotted alongside both DEF and TERM. Both HML and SMB appear relatively stationary despite the extreme volatility in the year 2000, while the DEF and TERM values display a hump-shaped pattern with the apex virtually bisecting the DT period. As suspected, the DEF and TERM factors are non-stationary.

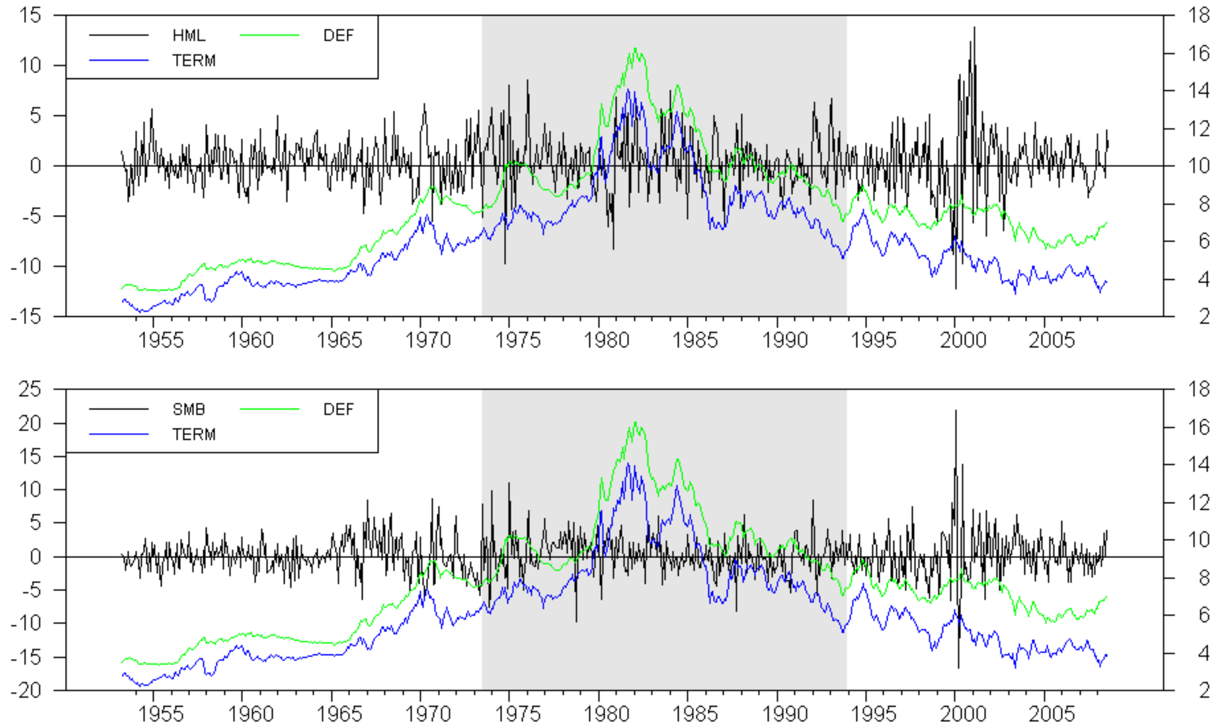

Figure 3

HML, SMB, and DEF from July 1926-August 2008

Figure 3 displays the time series for HML, SMB and DEF from July 1926-August 2008. This figure depicts a similar pattern as before for SMB and HML, verifying that the DT period represents an anomalous macroeconomic timeframe given the history of this recorded financial data. DEF levels during the DT period are almost universally higher than the other clear peak that occurred during the 1930s.

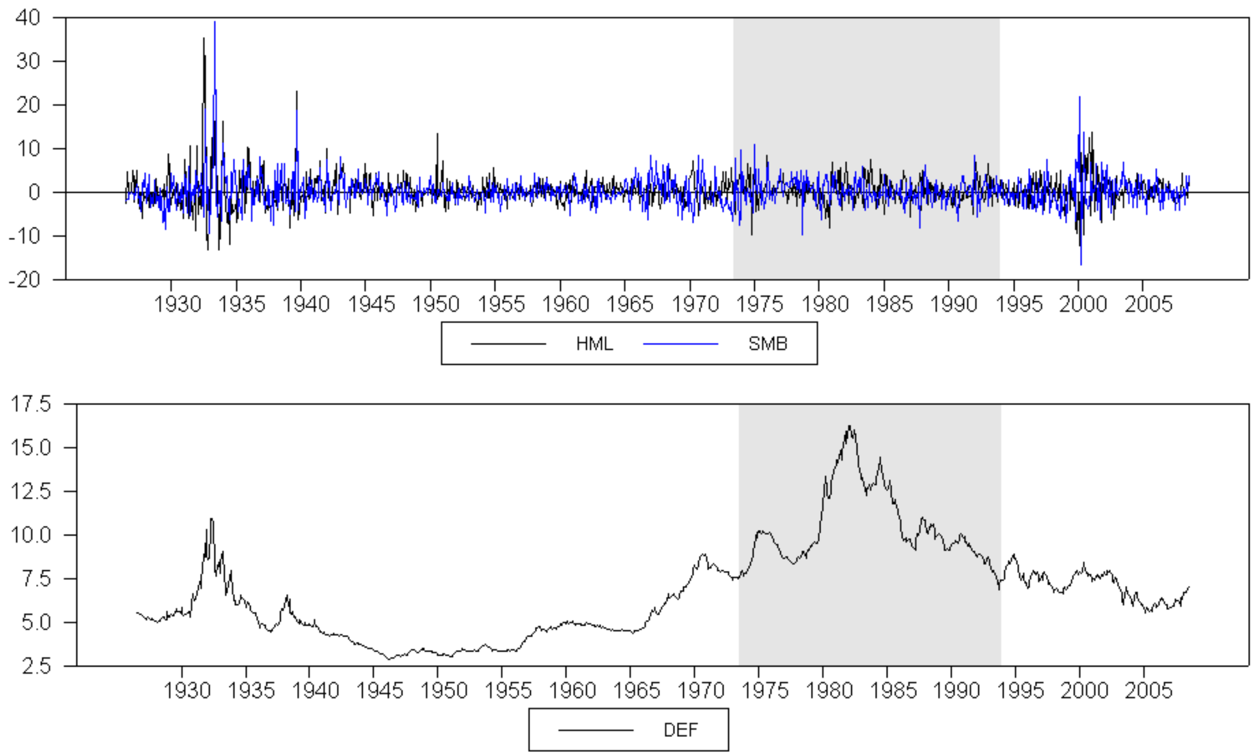

Figure 4
DEF Time Series (continuous plot) and Periods of Highest ΔDEF Decile (binary plots)

Figure 4 plots DEF as a continuous variable and ΔDEF as a binary value, where ΔDEF =1 when the DEF innovation is in the top decile. The overlap between the DT period and these high values of ΔDEF is apparent, and ΔDEF also appears to correspond with the other clear DEF "peak" in the early 1930s.

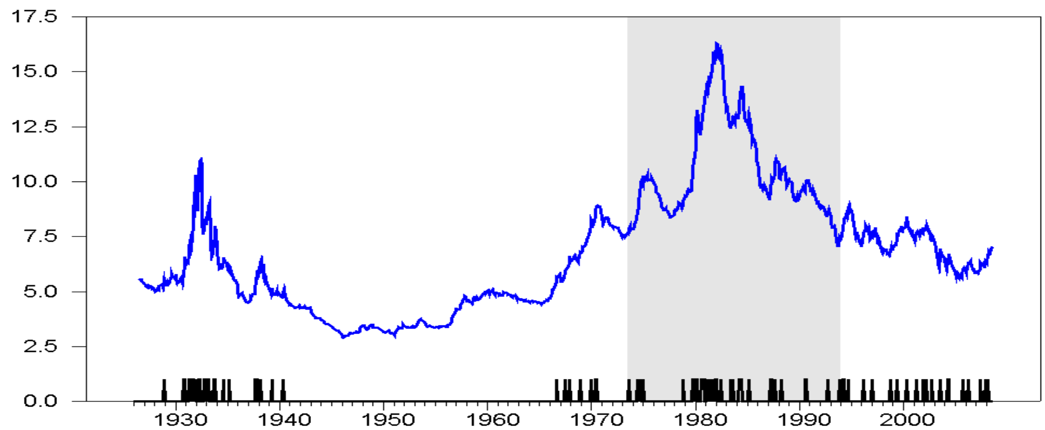

Table 1
Monthly Mean Excess Returns of Size and Book-to-Market Sorted Portfolios (63:07-93:12)

Table 1 shows the mean monthly excess return summary statistics for the 25 book-to-market sorted and size sorted portfolios, in percent. Please see Ken French's website for details about portfolio construction and measures. While not a perfect replication of returns from DT (1997) or FFD (2000), these returns appear virtually identical in trend—showing the size and value premia—and similar in value to both DT Table 1 and FFD Table II. For comparison purposes, Appendix 1 replicates the DT Table (see "All Months") and FFD Table II (see "Ex Ret" column for the 7/63-6/97 period).

		Book-to-Market				
		Low				**High**
	Small	0.253	0.720	0.735	0.929	1.107
		0.388	0.668	0.918	0.958	1.097
Size		0.424	0.741	0.706	0.905	0.999
		0.455	0.407	0.677	0.796	0.934
	Large	0.323	0.372	0.388	0.524	0.623

Table 2
HML loadings for the DT Period

Table 2 shows information about the HML factor loadings in the DT period relative to those in the non-DT period of this study, controlling for the SMB and market factors in a traditional three-factor model. Model (1) below shows the equation estimated.

$$R_{i,t} - R_F = \beta_0 + \beta_{i,HML}HML + \beta_{i,HML(DT)}HML \cdot DT + \beta_{i,SMB}SMB + \beta_{i,SMB(DT)}SMB \cdot DT + \beta_{i,M}(R_M - R_F) + \varepsilon_t \quad (1)$$

Panel A depicts the values for $\beta_{i,HML(DT)}$. Shaded values are significant at conventional levels (i.e., 90%). For those that are significant, Panel B depicts the percentage decrease change between $\beta_{i,HML}$ and $\beta_{i,HML(DT)}$. Shaded values indicate increases instead of decreases.

Panel A:Marginal HML Loadings in DT Period

		B/M				
		Low				**High**
	Small	-0.082	-0.021	-0.159	-0.191	-0.119
		-0.176	-0.229	-0.206	-0.209	-0.156
Size		-0.012	-0.161	-0.138	-0.245	-0.155
		-0.054	-0.304	-0.211	-0.095	-0.193
	Large	-0.129	-0.276	-0.204	-0.123	0.021

Pane B: Percentage Decrease in HML Loading from Non-DT to DT

	Low				**High**
Small	---	---	43.1	35.2	16.5
	-59.1	96.8	45.1	31.6	18.8
	---	67.7	27.3	33.0	17.5
	---	94.9	40.6	14.2	21.4
Large	-40.3	128.4	54.7	18.1	-2.5

Table 3
Marginal SMB loadings for the DT Period

Table 3 shows information about the SMB factor loadings in the DT period relative to those in the non-DT period of this study, controlling for the HML and market factors in a traditional three-factor model. Model (1) below shows the equation estimated.

$$R_{i,t} - R_F = \beta_0 + \beta_{i,HML}HML + \beta_{i,HML(DT)}HML \cdot DT + \beta_{i,SMB}SMB + \beta_{i,SMB(DT)}SMB \cdot DT + \beta_{i,M}(R_M - R_F) + \varepsilon_t \quad (1)$$

Panel A depicts the values for $\beta_{i,SMB(DT)}$. Shaded values are significant at conventional levels (i.e., 90%). For those that are significant, Panel B depicts the percentage decrease between $\beta_{i,SMB}$ and $\beta_{i,SMB(DT)}$. Shaded values indicate increases instead of decreases.

Panel A:

	B/M				
	Low				**High**
Small	-0.173	-0.118	0.003	0.023	0.140
	-0.080	0.054	0.076	-0.047	0.001
	-0.059	0.157	0.143	-0.001	0.107
	-0.101	0.092	0.156	-0.125	-0.023
Big	0.011	0.069	-0.099	0.001	-0.093

Panel B: Percentage Decrease in HML Loading from Non-DT to DT

	Low				**High**
Small	11.8	8.9	---	---	-13.2
	7.6	---	-10.0	---	---
	---	-32.2	-35.6	---	-20.3
	23.9	-43.7	-114.3	44.5	---
Big	---	32.0	-55.4	---	---

Table 4

Table 4 shows the results when scaling HML and SMB factor loadings with DEF during the DT period ($\beta_{i,HMLDEF}$ and $\beta_{i,SMBDEF}$, respectively) and controlling for the HML and market factors in a traditional three-factor model. Model (2) below shows the equation estimated.

$$R_{i,t} - R_F = \beta_0 + \beta_{i,HML}HML + \beta_{i,HMLDEF}HML \cdot DEF + \beta_{i,SMB}SMB + \beta_{i,SMBDEF}SMB \cdot DEF + \beta_{i,M}(R_M - R_F) + \varepsilon_t \quad (2)$$

Panel A depicts the values for $\beta_{i,HMLDEF}$ and $\beta_{i,SMBDEF}$ during the DT period. Shaded values are significant at conventional levels (i.e., 90%).

Panel B depicts the values for $\beta_{i,HMLDEF}$ and $\beta_{i,SMBDEF}$ during the non-DT period. Shaded values are significant at conventional levels (i.e., 90%).

Panel C depicts the differences in $\beta_{i,HMLDEF}$ and $\beta_{i,SMBDEF}$ from the DT period to the non-DT period. Shaded values indicate the DT and non-DT period values are significantly different at conventional levels (i.e., 90%) using a two-tailed difference of means test.

Panel A: DEF-Scaled Factor Loadings, DT Period

HML*DEF		Low				High
	Small	-0.063	-0.023	-0.010	-0.003	-0.023
		-0.028	0.000	-0.007	-0.013	-0.002
		0.003	0.011	-0.017	-0.011	-0.001
		-0.008	-0.072	-0.013	-0.010	0.020
	Big	0.043	-0.051	-0.077	0.000	-0.025
SMB*DEF		**Low**				**High**
	Small	-0.038	-0.032	0.000	0.009	-0.027
		-0.035	-0.018	-0.010	-0.002	-0.009
		-0.043	0.013	0.020	0.022	-0.010
		-0.023	-0.016	0.040	0.003	0.011
	Big	-0.001	-0.043	-0.041	0.024	-0.016

Panel B: DEF-Scaled Factor Loadings, Non-DT Period

HML*DEF		Low				High
	Small	0.232	-0.049	-0.055	0.026	-0.048
		-0.070	0.055	0.052	0.058	0.005
		0.057	0.010	0.053	0.056	0.030
		-0.008	0.032	0.020	0.092	0.047
	Big	0.016	-0.002	0.059	0.063	-0.155
SMB*DEF		**Low**				**High**
	Small	-0.321	0.311	-0.018	0.044	-0.029
		-0.083	0.057	0.048	0.007	-0.027
		0.055	-0.048	-0.068	-0.039	-0.067
		-0.015	-0.007	-0.009	-0.062	-0.009
	Big	-0.015	-0.016	0.022	0.029	-0.023

Panel C: DEF-Scaled Factor Loadings, Difference between DT Period and Non-DT Period

HML*DEF	Low				High
Small	-0.294	0.026	0.055	-0.026	0.025
	0.042	-0.055	-0.052	-0.058	0.000
	-0.057	0.000	-0.053	-0.056	-0.030
	0.000	-0.104	-0.020	-0.092	-0.047
Big	0.027	-0.051	-0.136	-0.063	0.155
SMB*DEF	**Low**				**High**
Small	0.283	-0.343	0.000	-0.044	-0.027
	0.048	-0.057	-0.048	0.000	0.027
	-0.098	0.048	0.068	0.039	0.067
	0.000	0.000	0.040	0.062	0.000
Big	0.015	-0.043	-0.063	-0.029	0.000

Table 5

Cross-Sectional Second-Pass Regressions for Models Including DEF

Table 5 shows the results from second-pass regressions shown in Models (3), (4), and (5) below across the whole period, DT period, and non-DT period. Please see Fama and MacBeth (1973) for additional details on this cross sectional procedure. ***, **, and * indicate parameters are significant at the 1%, 5%, and 10% levels.

$$(a) \quad \overline{R_\iota - R_f} = \lambda_0 + \lambda_{HML}\beta_{i,HML} + \lambda_{SMB}\beta_{i,SMB} + \lambda_{MKT}\beta_{i,MKT} + \varepsilon_t \qquad (3)$$

$$(b) \quad \overline{R_\iota - R_f} = \lambda_0 + \lambda_{HML}\overline{\beta_{\iota,HML}} + \lambda_{SMB}\overline{\beta_{\iota,SMB}} + \lambda_{MKT}\overline{\beta_{\iota,MKT}} + \varepsilon_t \qquad (4)$$

where $\overline{\beta_{\iota,HML}}$ is the mean of the time-varying HML loading over the respective time period; the same process generates the mean time-varying SMB and MKT loadings

$$(c) \quad \overline{R_\iota - R_f} = \lambda_0 + \lambda_{HML}\beta_{i,HML} + \lambda_{SMB}\beta_{i,SMB} + \lambda_{MKT}\beta_{i,MKT} + \lambda_{DEF}\beta_{i,DEF} + \varepsilon_t \qquad (5)$$

Panel A depicts the theoretically ideal pattern of significance for the various parameter estimates in these second pass, cross-sectional regression models.

Panel B depicts the results for the whole period and various sub-periods using the standard Fama and French three factor model shown in Model 3.

Panel C depicts the results for the whole period and various sub-periods using the standard Fama and French three factor model shown in Model 4, when the factors are conditioned using DEF in the first-pass model (see equation 2).

Panel D depicts the results for the whole period and various sub-periods using the standard Fama and French three factor model shown in Model 5, which adds the DEF factor as an independent, fourth factor.

Panel A: Ideal Pattern for FF 3 Factor Model 2nd Pass Regressions

	λ_0	λ_{HML}	λ_{SMB}	λ_{MKT}	Adj R^2
Time Period	Insignificant	Significant	Significant	Significant or 0	Near 1.0

Panel B: FF 3 Factor Model 2nd Pass Regressions

	λ_0	λ_{HML}	λ_{SMB}	λ_{MKT}	Adj R^2
Whole Period	2.251***	0.291*	0.275**	-1.591**	0.336
DT Period	0.279	0.523***	0.274***	0.281	0.747
Non-DT Period	2.464***	0.266	0.281**	-1.803**	0.265

Panel C: FF 3 Factor Model 2nd Pass Regressions with Factors Conditioned Using DEF

	λ_0	λ_{HML}	λ_{SMB}	λ_{MKT}	Adj R^2
Whole Period	2.134***	0.049**	0.020	-0.220***	0.321
DT Period	0.995***	0.043***	0.006	-0.036	0.447
Non-DT Period	2.513***	0.053*	0.029	-0.336***	0.340

Panel D: FF 3 Factor Model 2nd Pass Regressions with Additional Factor, DEF

	λ_0	λ_{HML}	λ_{SMB}	λ_{MKT}	λ_{DEF}	Adj R^2
Whole Period	2.103***	0.303**	0.220*	-1.400**	-3.247	0.363
DT Period	-0.041	0.306**	0.313***	0.664	2.965**	0.373
Non-DT Period	2.295***	0.374***	0.192***	-1.666***	1.982***	0.731

Table 6

Cross-Sectional Analysis when Scaling by High DEF Innovations

Table 6 shows the results from second-pass regressions shown in Model (7) across the whole period, DT period, and more general periods where DEF innovations, ΔDEF, are in their highest decile. Note, Model 6 is shown for completeness, as it shows the first-pass, time series model used to generate the respective beta values. Please see Fama and MacBeth (1973) for additional details on this cross sectional procedure. ***, **, and * indicate parameters are significant at the 1%, 5%, and 10% levels.

$$R_{i,t} - R_F = \beta_0 + \beta_{i,HML}HML + \beta_{i,HML(DT)}HML \cdot \Delta DEF + \beta_{i,SMB}SMB + \beta_{i,SMB(DT)}SMB \cdot \Delta DEF + \beta_{i,M}(R_M - R_F) + \varepsilon_t \quad (6)$$

$$\overline{R_\iota - R_f} = \lambda_0 + \lambda_{HML}\overline{\beta_{\iota,HML}} + \lambda_{SMB}\overline{\beta_{\iota,SMB}} + \lambda_{MKT}\beta_{i,MKT} + \varepsilon_t \quad (7)$$

where $\overline{\beta_{\iota,HML}}$ is the mean of the time-varying HML loading over the respective time period; the same process generates the mean time-varying SMB and MKT loadings

Panel A shows results for the conditioned models shown in (6) and (7) for the whole period, DT period, and more general periods when DEF innovations are at their highest values.

Panel B shows results for the standard FF three factor model when DEF innovations are at their highest levels. That is, the results stem from a process identical to model 3 but only during the time periods when DEF innovations are at their highest levels.

Panel A:

	λ_0	λ_{HML}	λ_{SMB}	λ_{MKT}	Adj R^2
Whole Period	2.648***	81.086	181.877**	-1.877**	0.192
DT Period	0.784	-638.426***	-418.352***	-0.269	0.649
ΔDEF Top Decile	-0.519	-4.274***	1.182*	-1.927	0.639

Panel B: Second Pass Regressions for Standard FF 3 Factor Model

	λ_0	λ_{HML}	λ_{SMB}	λ_{MKT}	Adj R^2
ΔDEF Top Decile	2.327	-1.186*	-0.389	-4.525*	0.173

Appendix 1
Reproduction of Daniel and Titman (1997) Table 1 and Davis, Fama, and French (2000) Table II

Daniel and Titman (1997)

Table I

Monthly Mean Excess Returns (in Percent) of Size and Book-to-Market Sorted Portfolios (63:07–93:12)

We first rank all NYSE firms by their book-to-market at the end of year $t-1$ and their market capitalization (ME) at the end of June of year t. We form quintile breakpoints for book-to-market and ME based on these rankings. Starting in July of year t, we then place all NYSE/Amex and Nasdaq stocks into the five book-to-market groups and the five size groups based on these breakpoints. The firms remain in these portfolios from the beginning of July of year t the end of June of year $t+1$.

Panel A presents the average of the monthly value weighted returns for each of these portfolios, net of the one month T-Bill return from the CRSP RISKFREE file. Panel B presents the average returns for January only, and Panel C presents the average return, excluding the returns in January.

	Low	Book-to-Market			High
Panel A: All Months					
Small	0.371	0.748	0.848	0.961	1.131
	0.445	0.743	0.917	0.904	1.113
Size	0.468	0.743	0.734	0.867	1.051
	0.502	0.416	0.627	0.804	1.080
Big	0.371	0.412	0.358	0.608	0.718
Panel B: Januarys only					
Small	6.344	6.091	6.254	6.827	8.087
	3.141	4.456	4.522	4.914	6.474
Size	2.397	3.374	3.495	3.993	5.183
	1.416	1.955	2.460	3.515	5.111
Big	0.481	1.224	1.205	2.663	4.043
Panel C: Non-Januarys only					
Small	−0.162	0.271	0.365	0.438	0.510
	0.204	0.412	0.595	0.545	0.635
Size	0.296	0.509	0.488	0.588	0.682
	0.420	0.278	0.463	0.562	0.720
Big	0.361	0.340	0.283	0.424	0.421

Davis, Fama, and French (2000)

Table II

Three-Factor Regressions for Portfolios Formed from Independent Sorts on Size and BE/ME

$$R_i - R_f = a_i + b_i(R_M - R_f) + s_i\text{SMB} + h_i\text{HML} + \epsilon_i$$

We form the portfolios here and in the following tables at the end of June of each year t (1929 to 1996) using all NYSE, AMEX, and Nasdaq stocks with nonnegative BE for year $t-1$, and at least 36 months of returns data in the five years ending in December of $t-1$. Here we allocate the stocks to three size groups (small, medium, or big; S, M, or B) each year based on their June market capitalization, ME. We allocate stocks in an independent sort to three book-to-market equity (BE/ME) groups (low, medium, or high; L, M, or H) based on BE/ME for December of year $t-1$. The breakpoints are the 33rd and 67th ME and BE/ME percentiles for the NYSE firms in the sample. We form nine portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H) as the intersections of the three size and the three BE/ME groups. The returns explained by the regressions, R_i, are the value-weight returns on the portfolios from July of year t to June of $t+1$. The t-statistics, $t(\,)$, for the regression coefficients (here and in all following tables) use the heteroskedasticity consistent standard errors of White (1980). Here and in all following tables: (i) BE/ME is the aggregate of BE for the firms in a portfolio divided by the aggregate of ME; (ii) Size is the value-weight average of the NYSE size percentiles for the firms in a portfolio; (iii) BE/ME and Size are averages of the annual values for the time periods shown; (iv) Ex Ret is the average monthly post-formation return in excess of R_f; (v) the regressions R^2 are adjusted for degrees of freedom.

	BE/ME	Size	Ex Ret	a	b	s	h	$t(a)$	$t(b)$	$t(s)$	$t(h)$	R^2
7/29–6/97												
S/L	0.55	22.39	0.61	−0.42	1.06	1.39	0.09	−4.34	30.78	19.23	1.73	0.91
S/M	1.11	22.15	1.05	−0.01	0.97	1.16	0.37	−0.18	53.55	19.49	9.96	0.96
S/H	2.83	19.05	1.24	−0.03	1.03	1.12	0.77	−0.73	67.32	39.21	26.97	0.98
M/L	0.53	55.85	0.70	−0.06	1.04	0.59	−0.12	−1.29	55.83	18.01	−4.30	0.96
M/M	1.07	55.06	0.95	−0.01	1.05	0.47	0.34	−0.15	32.98	17.50	9.50	0.96
M/H	2.18	53.21	1.13	−0.04	1.08	0.53	0.73	−0.90	47.85	8.99	11.12	0.97
B/L	0.43	94.65	0.58	0.02	1.02	−0.10	−0.23	0.88	148.09	−6.88	−13.52	0.98
B/M	1.04	92.06	0.72	−0.09	1.01	−0.14	0.34	−1.76	61.61	−4.96	13.66	0.95
B/H	1.87	89.53	1.00	−0.09	1.06	−0.07	0.84	−1.40	52.12	−0.86	21.02	0.93
7/29–6/63												
S/L	0.68	23.83	0.69	−0.53	1.01	1.47	0.23	−3.04	18.66	15.72	2.82	0.90
S/M	1.35	23.63	1.21	−0.01	0.96	1.24	0.38	−0.07	34.72	15.60	6.21	0.95
S/H	3.96	20.23	1.44	−0.03	1.02	1.17	0.83	−0.40	44.71	28.80	17.76	0.98
M/L	0.64	55.20	0.84	−0.08	0.98	0.56	0.01	−1.14	37.44	12.26	0.39	0.96
M/M	1.28	54.20	1.13	0.00	1.07	0.47	0.33	0.07	26.38	11.77	7.73	0.97
M/H	2.83	51.59	1.30	−0.07	1.07	0.50	0.79	−0.92	52.49	5.44	7.74	0.97
B/L	0.48	94.92	0.72	−0.01	1.02	−0.08	−0.20	−0.20	131.66	−4.89	−8.09	0.99
B/M	1.21	91.97	0.89	−0.09	1.00	−0.12	0.37	−1.20	43.96	−2.90	10.08	0.96
B/H	2.33	88.91	1.30	0.00	1.02	−0.12	0.97	−0.01	34.28	−0.96	17.99	0.94
7/63–6/97												
S/L	0.42	20.94	0.54	−0.22	1.06	1.22	−0.14	−3.31	60.47	39.87	−4.51	0.96
S/M	0.87	20.68	0.89	0.03	0.97	1.02	0.31	0.71	74.53	52.41	13.82	0.98
S/H	1.71	17.88	1.04	0.04	0.99	1.03	0.62	1.27	75.12	64.49	25.86	0.98
M/L	0.42	56.51	0.56	−0.02	1.07	0.58	−0.24	−0.33	71.73	27.08	−9.73	0.96
M/M	0.87	55.93	0.77	0.02	1.00	0.48	0.30	0.31	64.36	22.60	11.22	0.95
M/H	1.54	54.83	0.96	0.03	1.05	0.55	0.63	0.53	69.16	28.08	24.23	0.96
B/L	0.38	94.38	0.45	0.10	0.99	−0.15	−0.32	2.89	91.73	−8.92	−16.53	0.98
B/M	0.86	92.14	0.54	−0.04	0.99	−0.19	0.25	−0.70	55.19	−6.91	8.53	0.91
B/H	1.41	90.16	0.70	−0.13	1.04	−0.01	0.69	−2.59	76.64	−0.36	28.53	0.94

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