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The Influence of Productivity on Asset Pricing

Abstract

Ceteris Paribus, highly productive industries should translate into high economic growth and high expected returns. To test this, we create a productivity factor using industry-level total factor productivity estimates. This factor captures the difference in returns between industries with high productivity and industries with low productivity. On average, the productivity premium contributes 0.75 to 2.41 percent per annum for the range of productivity factors we construct, from July 1963 to December 2002. To test whether productivity drives the cross-section of stock returns, we augment standard asset pricing models with this productivity factor. Our results show that i) in accordance with our hypothesis, productivity has a bigger impact on smaller firms, and that growth firms have a higher productivity beta, and ii) productivity helps price assets even when size and book-to-market factors are included. Finally, we find that since 1990, firms in more competitive industries are more likely to show higher productivity and gain from it.

I. Introduction

This paper examines the link between productivity and the cross-section of stock returns. Classic works on determining the overall rate of “interest” in an economy, such as Ramsey (1928) and von Neumann (1945) firmly place as a primary determinant the rate of real economic growth in consumption per capita: high growth economies should have high expected rates of return and vice versa. In this way, the expected rate of return is needed to equilibrate the consumption and investment markets in a simple equilibrium. Whether or not real economic growth is high or low should in turn be related to productivity growth. *Ceteris Paribus*, highly productive economies translate to high economic growth and high expected rates of return. Although these early models did not deal with uncertainty, the intuition would then follow that uncertainty surrounding the rate of economic growth and productivity should be a primary factor in pricing risky assets. This intuition from the Ramsey-von Neumann literature has been increasingly reflected in the modern asset pricing literature.

In the original capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), investors maximized a single-period utility function defined over terminal wealth, where by construction as a single period framework this uncertain wealth was also equal to uncertain consumption. However, the key empirical result of the CAPM is that a security’s risk is measured relative to the return on a diversified market portfolio. Only when the single-period assumption of the CAPM was relaxed by Merton (1971), Rubinstein (1976), Lucas (1978), Stapleton and Subrahmanyam (1978) and Breeden (1979) was the immediate link between stock market returns and consumption clarified. Unless extreme restrictions are placed on the opportunity set, Merton et al. showed that

the link between an uncertain stock market return and uncertain consumption is broken and the primal is consumption, as in Ramsey and von Neumann. The key empirical result in these consumption-based capital asset pricing models (CCAPM) is that a security's risk depends not on uncertain stock market returns, but on the extent to which a security hedges aggregate consumption through economic growth.

The problem is that empirical support for both the CAPM and the CCAPM has been less than hoped for. For the CAPM, the well-known empirical findingsⁱ that expected returns on low beta firms are higher than the CAPM predicts while the expected returns on high beta firms are lower, has given rise to the Fama-French (1992, 1993) three-factor model. While factors such as size and book-to-market help explain a significant part of the cross-sectional variation in returns, it is still not clear whether these firm characteristics reflect risk differences or market imperfections. However, the factor mimicking technology introduced by Fama and French has revolutionized empirical asset pricing, and has largely displaced the direct use of economic variables as in Chen, Roll, and Ross (1986) and factor analysis itself as in Lehmann and Modest (1988).

The CCAPM, in contrast, has had problems finding empirical validation from the start.ⁱⁱ The cross-sectional explanatory power of unconditional CCAPM tests, as in Wheatley (1988), is incredibly low; a result also found by Breeden et al. (1989) and Mankiw and Shapiro (1986). Given the economic intuition underlying the CCAPM, there have been considerable efforts to try and resurrect its poor empirical performance. Harvey (1989), Harvey and Siddique (2000), and Kandal and Stambaugh (1990) all attempt to estimate a conditional asset pricing model; Harvey for the CAPM and Kandal and Stambaugh for the CCAPM. In both cases the cross-sectional tests are conditioned on

business cycle effects to adjust for changing risk premia. However, the results, while better are still unsatisfactory. This has led to efforts at incorporating more factors into the pricing model.

Epstein and Zin (1991) preferences have been used to introduce durable and non-durable goods as in Yogo (2006), whereas another approach has been to add additional state variables. A partial list includes uninsured idiosyncratic risk examined by Constantinides and Duffie (1996), housing by Piazzesi et al. (2003), production by Cochrane (1991), and lagged consumption by Campbell and Cochrane (1999). Our paper follows this line of literature and is similar in spirit to Balvers and Huang (2007), who argue that in a competitive complete market economy the marginal rate of substitution in consumption of the representative agent is the same as the marginal rate of inter-temporal transformation, that is, the rate of return on investment as in the early certainty model of Hirshleifer (1958). However, Balvers and Huang implement this idea through the sensitivity of a security to an external productivity shock.

In contrast, this paper makes use of industry level productivity data created as a result of joint work by the National Bureau of Economic Research (NBER) and the U.S. Census Bureau's Centre for Economic Studies (CES). We describe the data more fully later but it includes three- and four-digit SIC industry total factor productivity estimates for US manufacturing. By creating factor mimicking portfolios with respect to productivity, we introduce a stock market factor that mimics the driving force behind the CCAPM. In this way, we include the primal driver in the CCAPM as a stock market factor in the CAPM. This captures the intuition that it is the stock market reaction to productivity changes, in causing uncertain capital gains and losses that causes risk, rather

than the productivity changes themselves. This is important since it is difficult to capture uncertain capital gains and losses in a representative agent economy.ⁱⁱⁱ

An additional motivation for creating a productivity factor is that productivity has a heterogeneous impact on the economy and the stock market. Shumpeter (1942) in his classic work recognized the “creative destructive” forces of capitalism generated by productivity or technological change. These forces primarily affect young firms as new industries are created and old ones die. For example, Chamberlin et al. (2002) looked at how productivity changes affected the stock market during the Internet boom, which was primarily driven by young start-ups. Further as the RBC Financial Group notes in a research report^{iv} “looking at productivity growth by firm size, two observations can be drawn. First, in 39 of 70 industry classifications, or 56 percent of industries, micro employers had faster productivity gains than the industry average. This suggests that more often than not, relatively small firms have led bigger firms in productivity growth. Second, this view that productivity growth was driven largely by consolidation among firms is further underscored....”

This suggests that industry life cycle effects caused by productivity changes predominantly affect small firms, where the productivity impact is more apparent and immediate, and also where balance sheets are more immature. It is in the nature of start-ups that book equity has not been built up through retained earnings and a consistent history of profitability. As such productivity may affect the Fama-French size and book to market factors, as well as the overall market return. Examining the impact of productivity differences across industries, therefore, raises the possibility of understanding why the Fama-French firm characteristics may reflect risk factors.

Although productivity is shown to be a significant risk factor even after size and value premium are controlled, we also find that the impact of productivity premium on firms is not universal. Instead, it has higher impact on small and growth firms. We also show that SMB and HML do catch priced information that is unrelated to productivity.

How well does our model work? The downside is that it is not the holy-grail that solves the asset pricing puzzle. The upside is that productivity is a priced factor. We find that the productivity factor affects the overall market return and that on average it contributes 0.75 to 2.41 percent annually, for the range of productivity factors we constructed. This is a similar order of magnitude to the size premium, but less than the book-to-market premium. Further, we show that productivity is priced even when the market excess return and factors based on size and book-to-market are included in standard asset pricing tests. However, while the importance of size is reduced, book-to-market is still important. So considering a productivity factor brings the CAPM and CCAPM closer together, but a gap still exists.

The plan of the remainder of the paper is as follows. Section II discusses our model, our data and summary statistics. Section III then describes our asset pricing tests, before we add our conclusions and suggestions for further research. Section IV extends the analysis to discuss competition and the role of industry concentration modelled by the Herfindahl index. Section V provides conclusions.

II. The Model, Data, and Summary Statistics

Asset pricing models are normally based on the first-order condition for a representative agent maximizing a von-Neumann–Morgenstern expected utility function, that is, for any security j ,

$$E(\gamma(1 + R_j)) = 1 \quad (1)$$

where R_j is the return on the j th risky asset, and γ is the marginal rate of substitution between time periods 0 and 1.^v Expanding the expectation and assuming approximate normality, Rubinstein (1976) showed that (1) can be reformulated as an asset pricing model,

$$E(R_j) = r_f + aCov(z, R_j) \quad (2)$$

where the risk free rate, should one exist, is defined by the inverse of the expected marginal utility in time period 1 and a is a measure of the investor's Pratt-Arrow absolute risk aversion.

Equation (2) can be simplified in many ways. If the argument of the investor's utility function, z , is consumption, then the marginal rate of substitution is determined based on consumption, as in the CCAPM. If, in contrast, the argument is uncertain wealth, then the argument is the return on a market portfolio as in the CAPM. If we take an a theoretical approach and simply define z as a linear function of various risks in the economy, we get a linear pricing model. For three factors we get,

$$E(R_j) = r_f + a_1 Cov(F_1, R_j) + a_2 Cov(F_2, R_j) + a_3 Cov(F_3, R_j)$$

This results in a standard multi-factor model where the expected return on the j^{th} security is equal to the risk free rate plus a series of risk premia determined by the covariance of the security's return with that on each risk factor. From the factor analysis of Lehmann and Modest (1988), we would expect there to be at most three or four factors. The return on the market portfolio would be one factor, where following Cochrane (1991) and in the spirit of Hirshleifer, Ramsey, and von Neumann, the stock market return in a complete market is equal to the return on investment. The two or three additional risk factors can then be viewed as hedging portfolios in the spirit of Merton, Stapleton and Subrahmanyam, and Breeden. One such hedging portfolio would be the return on a productivity factor which shifts the aggregate production function and thus the return on investment.

The empirical specification in this paper is therefore to first consider the empirical relevance of productivity and its impact on the overall stock market, second to consider a two-factor model of the market return and productivity shocks, and finally to consider the productivity factor within the context of the standard Fama-French three-factor model to see whether the size and book-to-market factors are proxying for the more primal productivity factor.

The productivity data come from the National Bureau of Economic Research and U.S. Census Bureau's Center for Economic Studies Manufacturing sector Database. This database contains annual industry-level data on output, employment, payroll and other

input costs, investment, capital stocks, total factor productivity (TFP), and various industry-specific price indexes. The database covers all 4-digit manufacturing industries from 1958-2002, where we use the five-factor productivity estimate as our measure of productivity.^{vi} We do not use firm level productivity for two reasons. First, firm-level data is not publicly available, and second, there are many measurement issues regarding firm-level data.

Bartlesman and Gray (1996) describe the NBER productivity database where five-factor TFP is measured as follows:

$$TFP = Q - \sum_{i=1}^5 \alpha_i X_i$$

where Q is real output, α_i is the share of factor i in terms of revenues, and X_i is the output of factor i , expressed in terms of log first differences. The five factors are: capital, production worker hours, non-production workers, non-energy material, and energy. TFP growth is then estimated as the growth rate in real output minus the average growth rate from the five inputs, where the shares come from the Annual Survey of Manufacturers, with the capital share being the residual so the shares sum to one. In all cases the growth rates are expressed in real terms, so the productivity growth variable is an estimate of real productivity growth.^{vii}

The NBER productivity database uses 1987 SIC codes containing 459 4-digit industry definitions. Our stock market data are from the CRSP database. The time period used is from July 1963 to December 2002. Although the productivity data start in 1958, the data merge between NBER and CRSP leaves only one industry in the manufacturing

sector for the period from January 1958 to December 1962, which makes the study of cross-sectional industry returns impossible for that period. Our analysis therefore begins in 1963. Since the productivity mimicking portfolio is constructed at the end of June each year, the return data start from July 1963. This date is also the start month of the Fama-French factors, so our results can be more readily compared to those for other asset pricing models in the literature. Panel A of Table 1 reports the number of industries within the manufacturing sector per year and the number of firms per industry per year.

[Table 1]

Value-weighted and equally-weighted returns are constructed from July 1 in year t to June 30 in year $t+1$, to coincide with the Fama-French factors. These returns are matched to productivity in the calendar year $t-1$. This is to allow a recognition lag, so that productivity changes can be absorbed by the market in the same way as for the Fama-French factors.

The NBER productivity database also provides capital stock data at the 4-digit SIC industry level. To give an overview of the importance of productivity, we first construct a capital stock-weighted productivity growth index for the manufacturing sector as a whole. Figure 1 shows the annual stock market return and the productivity growth for the manufacturing sector from 1963 to 2002. The casual empiricism of Figure 1 indicates that stock returns vary positively with productivity growth: the higher the productivity growth, the higher the stock returns; and vice versa. This relationship seems particularly strong in the post-1982 period, when the real effects of productivity changes are not swamped by the significant inflation rates prior to then.^{viii}

[Figure 1]

Panel B of Table 1 shows the importance of the manufacturing sector. We include three “snapshot” years: 1963, the start of the sample, 1983 as the middle, and 2002 as the end of the period. The CRSP market portfolio includes stocks from NYSE, AMEX, and NASDAQ. In 1963, 50 percent of the firms in CRSP were manufacturing firms and they represented 56 percent of the market capitalization. By 2002, these proportions had decreased dramatically to only 16 percent of the firms with 34 percent of the market capitalization. The larger capitalization, as compared to simple firm weights, indicates that the size of the firms in the manufacturing sector is larger than that in other sectors. Further, the decline in the importance of manufacturing over this period is also suggestive of the changing importance of other firm-level characteristics, which apart from the disappearing dividends result of Fama-French (2001), has not hitherto been noted.

Table 2 reports the average annual productivity level, the stock price index, firm size, book-to-market ratios, as well as the average correlation among these variables. The total sample includes 10,741 4-digit SIC industry-year observations. We also calculate the Herfindahl index for each industry to see whether profit increases due to productivity changes are competed away in more competitive industries, thereby reducing any impact on stock market returns. For each industry-year observation, we define the variables as follow:

- We measure industry productivity by the annual 5-factor total productivity estimate in the NBER-CES Manufacturing Industry database. For Table 2, the productivity level is normalized to one in 1963.

- For Table 2, the stock price level is also normalized to one in 1963. We construct the industry price index by one plus the cumulative return since 1963.
- The degree of competition is measured by the Herfindahl index, which is the sum of squared shares of each firm, measured using market capitalization. Hou and Robinson (2006) and Massa, Rehman and Vermaelen (2007) measure industry concentration using the Herfindahl index.^{ix} The higher the Herfindahl index, the more concentrated is the industry, and hence the increased likelihood of reduced competition, as the stock market capitalization is divided among fewer firms.

Panel A in Table 2 shows that over this long period, there has been persistent growth in productivity, stock market value, and firm size. Interestingly, the correlation between the average productivity level and the Herfindahl index has not been consistently positive or negative. Before the 1990s, the correlation was generally positive indicating that there was greater productivity growth in less competitive industries dominated by large firms, but since then the correlation has turned negative. Even though the relationship is at best weak (only the correlation coefficients from 1996 to 1998 are statistically significant), this pattern is suggestive of the emergence of new industries in the 1990s during the technology and internet boom. Prior to that, the technology advance was pioneered by established firms with significant market power and high Herfindahl index values. However, since then the pattern has changed.

[Table 2]

Panel B of Table 2 reports the average correlation among these variables where there is an obvious common trend. For example, the productivity level is highly positively correlated to the stock price index (0.831) and firm size (0.96), but negatively correlated to book-to-market (-0.409).

To examine the impact of productivity, we create a factor-mimicking portfolio in the style of Fama-French to capture the productivity premium. To do this, we first calculate the monthly equally-weighted return for each 4-digit SIC industry. We use equally-weighted returns because our hypothesis is that productivity is driven predominantly by smaller firms. We then rank each industry according to their productivity in calendar year $t-1$, and assign the rank to stock returns from July of year t to June of year $t+1$. Using July to construct portfolios is consistent with Fama and French (1993). Finally, we calculate the difference between the mean of the industry return in the top productivity quintile and that in the bottom quintile for each month from July in year t to June of the following year. We name this factor PFSIC4Q, that is, the productivity factor formed on SIC 4-digit productivity quintiles (top quintile minus bottom quintile equally-weighted portfolios).

We use PFSIC4Q as the return on the factor mimicking portfolio throughout this paper. As a robustness check, we also construct alternative factors. For example, we repeat the above procedures for 3-digit SIC industries, we use deciles instead of quintiles, and value-weighted average returns in addition to equally-weighted returns. Productivity data are only available for manufacturing firms. Measuring productivity in service industries is particularly challenging due to the difficulty in measuring outputs, as well as

measuring labour inputs.^x For comparison, we also calculate the industry SMB and HML for the manufacturing sector using the Fama-French methodology.

Table 3 reports the summary statistics for PFSIC4Q and several alternative specifications. The average excess return ranges from 0.75 to 2.41 percent per year, close in magnitude to the SMB for manufacturing firms. Consistent with our argument, most of the productivity factors are positively correlated with SMB, and all of them are negatively correlated with HML. So in general terms we can say that productivity does affect returns in the capital market and that as we hypothesized it is closely related to the Fama-French size and book-to-market factors.

[Table 3]

The bottom panel of Table 3 indicates that the Fama-French size factor, SMB, for manufacturing firms generates 1.94 percent annually in average excess returns, while the Fama-French book-to-market factor, HML, generates 4.22 percent. Although SMB and HML for manufacturing firms have smaller excess returns compared to those from the full CRSP sample from Kenneth French's website, they are still high correlated: the correlation between SMB for manufacturing and SMB for the whole CRSP data base is 0.94, while for HML it is 0.73.^{xi}

III. Can Productivity Help Explain Stock Returns?

III.A. Factor Loading on Productivity Portfolios

To see whether productivity helps explain stock returns, we first consider the following two-factor time-series model:

$$R_t = \alpha + \beta_{PF} \times PFSIC4Q_t + \beta_m \times e_{-}R_{mt} + \varepsilon_t,$$

where R_t is the monthly excess return, $PFSIC4Q_t$ is the productivity factor, and $e_{-}R_{mt}$ is the residual from the following regression:

$$R_{mt} = \alpha + \beta_{PF} \times PFSIC4Q_t + e_t,$$

where R_{mt} is the monthly CRSP value-weighted excess return, and ε_t and e_t are standard random error terms.

The above specification is designed first of all to test the hypothesis that productivity affects security returns as Figure 1 indicates. In particular, we expect the productivity factor to have a bigger impact on small firms and on growth (i.e., low B/M) firms. Then we test whether the market excess return still has an impact on security returns after controlling for productivity.

We conduct the empirical tests with the return on three different portfolio groups as the dependent variable, R_t . The first group consists of 10 equally-weighted portfolios sorted by size, the second consists of 10 equally-weighted portfolios sorted by B/M, and finally, the third consists of 25 equally-weighted portfolios sorted by both size and B/M. This method is identical to that in Fama and French (1993), except that our sample only includes manufacturing firms.

Panel A of Table 4 has the results for the first set of portfolios sorted by size. In the two-factor model, the coefficient of the productivity factor, β_{PF} , is highly significant, and its magnitude decreases monotonically with size. In accordance with our hypothesis, productivity has a bigger impact on smaller firms than larger ones. The coefficient of the residual of the market excess return, β_m , is also significant, but its impact is fairly uniform across different size and B/M portfolios. Overall, the positive impact of

productivity on small firms is strong. The correlation between the average excess return on each size portfolio and its corresponding productivity beta is high at 0.839.

[Table 4]

Panel B of Table 4 has the results for portfolios formed on B/M deciles. Again, β_{PF} is positive. However, the relationship between B/M and β_{PF} is non-linear and approximately U-shaped: both very high and very low B/M portfolios have positive and significant productivity betas. One would expect low B/M, that is, high growth stocks to be correlated with high productivity, but the relationship for high B/M firms is a surprise. One explanation is the indirect relationship through size, that is, B/M may be correlated with size.

In order to disentangle the effects of productivity on B/M and size, Panel C of Table 4 has the results for the 25 portfolios formed on both size and B/M quintiles. Again, β_{PF} decreases with size. However, more importantly, we are able to isolate the impact of productivity on B/M by examining the beta pattern within each size quintile. For each size portfolio, B/M has in general, a negative relationship with the productivity beta. That is, growth firms have a higher productivity beta, as we hypothesized.

These results support Shumpeter's argument that productivity changes generate new industries (captured here by small, growth firms) and the destructive forces of capitalism make them risky.

Next, we consider an alternative factor model. Fama and French (1993) find that SMB and HML are able to explain the cross-section of stock returns for the period 1963-1990, so we now test for the extent to which SMB and HML are proxies for the productivity factor, and whether it continues to matter in a Fama-and-French setting.

Since SMB and HML are correlated with productivity, we first regress SMB and HML separately on PFSIC4Q, and use the residuals in a four-factor model. The residuals capture the variations in SMB and HML that are unrelated to the variations in productivity. The four-factor model we employ is specified as follows:

$$R_t = \alpha + \beta_m \times e_{-R_{mt}} + \beta_{SMB} \times e_{-SMB_t} + \beta_{HML} \times e_{-HML_t} + \beta_{PF} \times PFSIC4Q_t + \varepsilon_t$$

where e_{-SMB_t} and e_{-HML_t} are monthly residuals from the regressions:

$$SMB_t = \alpha + \beta_{PF} \times PFSIC4Q_t + e_t$$

$$HML_t = \alpha + \beta_{PF} \times PFSIC4Q_t + e_t$$

Table 5 presents the results from the models above. Note that the residuals of SMB and HML have statistically significant explanatory power, suggesting that in addition to proxying for productivity, size and book-to-market are robust risk factors in their own right.

[Table 5]

III.B. Asset Pricing Tests

The previous tests provide informal evidence that productivity helps explain the cross-section of security returns. We now turn to two formal asset pricing tests: the classic two-pass Cross-Sectional Regression (CSR) model^{xii} and the Stochastic Discount Factor (SDF) model.

The two-pass CSR model that we adopt involves the following two steps: a time-series regression for *each* portfolio, in which we estimate the portfolio betas, and a cross-

sectional regression, in which we estimate the risk premium of each factor. We can summarize this methodology as follows.

$$R_{it} = \alpha_i + \beta_i' f_t + \varepsilon_{it}$$

$t = 1, 2, \dots, T$ for each i

$$\overline{R}_i = \hat{\beta}_i' \lambda + \varepsilon_i$$

$i = 1 \dots n$

where R_{it} is the excess return on portfolio i in month t , \overline{R}_i is the average monthly excess return on portfolio i , f_t is a vector of risk factors, β_i is a vector of factor loadings, λ is a vector of risk premiums, n is the number of portfolios, and T is the number of monthly observations in the sample.^{xiii}

Because the betas estimated in the first step are used as regressors in the second step, there is an issue with “errors in variables”. To alleviate this problem, we adjust the standard errors of λ in the second step as proposed by Shanken (1992). Shanken shows that although the betas are estimated with errors, the errors tend to zero as T goes to infinity, and the estimate of λ is T -consistent when the adjustment is made. We also estimate the cross-sectional regression in the second step using Generalized Least Squares (GLS), to account for the fact that the residuals in second step may be correlated with each other. Further, to assess whether the linear asset pricing model is correctly specified, we report Shanken’s (1985) Cross-Sectional Regression Test (CSRT) statistic. This statistic measures the aggregate expected return errors, and its finite sample distribution under the null hypothesis is provided by Shanken.

The other asset pricing test we perform uses the Stochastic Discount Factor (SDF) approach, which is implemented using the Generalized Method of Moments (GMM)

pioneered by Hansen (1982). The GMM method is widely used in asset pricing tests, including Jagannathan and Wang (1996, 2002, and 2007), Jagannathan, Kubota, and Takehara (1998), Campbell and Cochrane (2000), Lettau and Ludvigson (2001), Hodrick and Zhang (2001), Farnsworth, Ferson, Jackson, and Todd (2002), Dittmar (2002), among others. As discussed in Cochrane (2001), there is no consensus on whether the two-pass CSR regression approach outperforms the SDF approach or vice versa. Hence, we perform both tests.

The SDF approach directly tests equation (1), which in excess return format is:

$$E(\gamma R_i) = 0$$

where γ is the SDF, and R_i is the excess return of portfolio i . The tradition is to specify the SDF as a linear function of a series of factors, i.e.,

$$\gamma = a + b'f,$$

where f is a vector of factors, a is a constant, and b is a vector of parameters. Kan and Robotti (2008) point out that this specification is somewhat problematic, because the specification test statistic is not invariant to an affine transformation of the factors, and the SDFs of competing models can have very different means. In contrast, an alternative specification that defines the SDF as a linear function of the de-meaned factors is free from these two problems, and is more appropriate for model comparison. Following Kan and Robotti, we define γ in terms of the de-meaned factor as:

$$\gamma = 1 - (f - e[f])'b .$$

As Cochrane (2001) explains, when factors are correlated we should test $b_j=0$, to see whether or not to include factor j in an asset pricing model, rather than test $\lambda_j=0$. This is because λ_j captures whether factor f_j is priced, whereas b_j captures whether

factor f_j is marginally useful in pricing assets, given the other factors. If we reject $b_j=0$, then we should include factor f_j when we price assets. Therefore, we test whether the SDF coefficient $b_j=0$ for the productivity portfolio, and following Cochrane (2001), we compare the risk premium estimates of λ with the corresponding two-pass CSR estimates.

The literature compares the performance of competing asset pricing models using the Hansen and Jagannathan (1997) distance measure (the HJ-distance). There are two nice interpretations of the HJ-distance. The first is that the HJ-distance measures the minimum distance between the proposed SDF and the set of correct SDFs. The second is that it presents the maximum pricing error of a portfolio of excess returns that has a unit second moment. The smaller is the HJ-distance measure, the smaller is the pricing error. Kan and Robotti (2008) suggest that a modification of the traditional Hansen-Jagannathan distance (HJ-distance) measure is needed when de-meaned factors are employed. Their modified HJ-distance uses the inverse of the covariance matrix (instead of the second moment matrix) of excess returns as the weighting matrix to aggregate pricing errors. We apply the modified Hansen-Jagannathan distance (HJM) to compare model performance in this paper.

Two hypotheses are examined in the asset pricing tests. The first is that productivity helps price assets in the presence of other factors, and the second is that the Fama-and-French factors, SMB and HML, are proxying to varying degrees for productivity. To do this we estimate four different models and compare their results:

Model 1 (CAPM):

$$R_t = \alpha + \beta_m \times R_{mt} + \varepsilon_t$$

Model 2 (Fama and French):

$$R_t = \alpha + \beta_m \times R_{mt} + \beta_{SMB} \times SMB_t + \beta_{HML} \times HML_t + \varepsilon_t$$

Model 3 (Fama and French with PFSIC4Q):

$$R_t = \alpha + \beta_{PF} \times PFSIC4Q_t + \beta_m \times R_{mt} + \beta_{SMB} \times SMB_t + \beta_{HML} \times HML_t + \varepsilon_t$$

Model 4 (Orthogonalized Fama and French with PFSIC4Q):

$$R_t = \alpha + \beta_{PF} \times PFSIC4Q_t + \beta_m \times e_{-}R_{mt} + \beta_{SMB} \times e_{-}SMB_t + \beta_{HML} \times e_{-}HML_t + \varepsilon_t$$

All dependent variables in the above equations are excess returns. We use the CAPM (Model 1) and the Fama and French model (Model 2) as benchmarks. Model 3 is the Fama and French model augmented with the productivity factor. In Model 4, we use the residuals for the three Fama-French factors after the direct impact of productivity is removed.

Since we use the Fama-French factors as a benchmark, the portfolio returns have to exhibit maximum dispersion across productivity, size, and B/M. To obtain maximum dispersion against all three variables, we perform a three-way independent sort. All equities in our sample are sorted into three portfolios according to productivity, size, and B/M. Twenty seven equally-weighted portfolios are formed from the intersection of the three independent sorts. Each portfolio has 474 monthly observations. Table 6 displays the formation and the mean excess return of each portfolio.

[Table 6]

The results from Model 1 to Model 3 are as follows. Panels A and B of Table 7 shows the test results from the SDF approach, with Panel A for the vector of SDF coefficients, b , and Panel B for the vector of risk premiums, λ . First, the SDF coefficient estimate of the productivity factor is positive and significant at the 5 percent level in

Model 3, which is the Fama-French three-factor model augmented with the productivity factor. This result suggests that the productivity factor helps price assets, even in the presence of the Fama-French factors. Second, Panel A shows that HML is significant in all models, while *SMB* is never significant. Finally, the probability value of the HJM distance measure is close to zero, rejecting the hypothesis that the aggregate pricing error is zero at the one percent level. It appears that there are other factors that may be important in explaining the cross-sectional variations in equity returns that are not considered here. Among all the models, the HJM distance measure for Model 3 is smaller than for either the CAPM or the Fama-French model. This means that any misspecification present in Model 3 translates into a smaller annualized pricing error as compared to the two standard asset-pricing models used in the literature.

[Table 7]

Figure 2 plots the productivity beta, or the loading on the productivity factor, of each of the 27 portfolios from Models 3. The portfolios are ordered according to Table 6. The productivity betas are positive and significant in all of the portfolios. Further, they monotonically decrease with size, but the relationship with B/M is not as clear. However, within each of the size-B/M portfolio, the loading is the highest in the highest productivity portfolio.

[Figure 2]

Panels C of Table 7 gives the estimates of the risk premiums from the two-pass GLS cross-sectional regression model. Again, they confirm the findings of the SDF approach. First, the risk premium on productivity is positive, and it is significant at 10 percent in Model 3, which is the Fama-French three-factor model augmented by the

productivity factor. Second, *HML* is positive and significant, indicating that it is priced. Finally, Panel C of Table 3.7 also reports that Shanken's (1995) CSRT statistics are significantly different from zero at one percent, again suggesting model misspecification.

Next, we examine the test results of Model 4. Model 4 explores the reason why SMB and HML explain the cross-section of stock returns. More specifically, it asks the following question: are *SMB* and *HML* proxies for productivity? The residual information in *SMB*, and the residual information in *HML* capture the information in the size and value premia that is unrelated to productivity. Interestingly, both SMB and residual of SMB are insignificant in both approaches, suggesting that *SMB* is not priced. In contrast, the residual from HML is positive and significant in all Panels of Table 7, suggesting that residual information in HML price stocks as well.^{xiv}

Interestingly, the estimates of the risk premiums are almost identical (and identical to up to four digits) in the SDF approach and the 2-step GLS cross-sectional regression approach. This comparison confirms Cochrane (2001) and Jagannathan and Wang (2002) that the apparently "new" SDF method is almost exactly the same as the traditional cross-sectional method.

The inescapable conclusion that emerges is that productivity is a significant risk factor, even when the Fama-French factors are included. However, while SMB and HML contain some productivity-related information, this information does not appear to be the reason that the Fama-French model is able to explain the cross-section of equity returns.

We have shown that productivity is a statistically significant risk factor. An important question to ask is whether it is economically significant. Following Harvey and

Siddique (2000), we conduct the following two evaluations. The first assesses on the impact of productivity on the model's pricing errors, and the second measures the expected return implied by a change in the productivity premium.

First, we consider the root mean squared in-sample pricing error (RMSE). We compare each model's RMSE from the two-pass GLS approach, using the CAPM's RMSE as a benchmark. In an unreported table, we find that without the productivity factor, the Fama and French model reduces the benchmark RMSE by 39 percent. Adding the productivity factor to the Fama and French model reduces the benchmark RMSE by another 9 percent. Hence, even in the presence of *SMB* and *HML*, productivity does appear to contain important pricing information.

The second evaluation assesses the impact of ignoring productivity on returns. As shown in Model 4, Panel C of Table 7, the productivity premium is 0.0027 per month. If we multiply it by one cross-sectional standard deviation (i.e., the standard deviation of the productivity betas estimated in the first step of the two-pass GLS approach), it translates into a 1.28 percent excess return on an annual basis.

IV. Productivity and Market Structure

The Herfindahl Index measures the degree of concentration in each industry. The smaller the Herfindahl index, the larger the number of firms in the industry, and hence there is likely more competition. There are two opposite arguments about the relation between the Herfindahl index and the cross-section of stock returns. The first is that in a more competitive industry, firms use more advanced technologies to improve productivity. As a result, the product of the Herfindahl index and productivity should

have a negative relationship to stock returns. The alternative argument is that, in an industry a concentration of market power (ie a high Herfindahl index), larger firms have the capability, in terms of both capital, to use the latest technology to increase productivity.

We test the impact of the product of the Herfindahl index and productivity on the cross section of industry returns. The manufacturing sector includes exactly 20 2-digit SIC industries each year, so we calculate the equally weighted monthly returns for each 2-digit SIC industries. Since Table 2 reveals the correlation between productivity and the Herfindahl index changes sign around 1990, we divide the sample into two sub-periods in 1990 and run a pooled OLS regression on the panel data.

Table 8 shows the test results. The loading on the productivity itself is always positive and significant in the two sub-samples. However, the sign of the coefficient estimate of the product changes from insignificantly positive to significantly negative in 1990. In an unreported test, we do the same test using 4-digit SIC industry portfolios and find the productivity coefficient changes from insignificantly negative to significantly negative. It seems that since 1990, it is firms in more competitive industries that are more likely to show higher productivity and gain from it. We acknowledge that in such a times-series cross-sectional setting, we need to be cautious about the OLS t-statistics since they are usually over-stated. However, we believe that the results still provide insight on the impact of industry competition and productivity on equity returns.

[Table 8]

V. Conclusion

In his paper, we examine the effect that industry productivity may have on equity returns. We create a productivity factor using 3- and 4-digit industry total factor productivity estimates from the NBER-CES database. This factor captures the difference in returns between industries with high productivity and industries with low productivity. On average, the productivity premium contributes 0.75 to 2.41 percent per annum for the range of productivity factors we construct, from July 1963 to December 2002.

Productivity is more likely to come from small and growth firms. Indeed, we find that the productivity factor is positive correlated with the Fama and French size premium, SMB, and negatively correlated with their value premium, HML. In both a CAPM and a Fama and French framework augmented by the productivity factor, we find that for the 10 portfolios sorted on size, the productivity beta decreases monotonically with size. In accordance with our hypothesis, productivity has a bigger impact on smaller firms than on larger ones. We also find that within each size portfolio, the productivity beta is higher in lower book-to-market portfolios. That is, growth firms have a higher productivity beta.

We also examine through asset-pricing tests whether productivity is priced, and we find that it is indeed, even after controlling for SMB and HML. Our results show that, although SMB and HML contain some productivity-related information, this is not the reason that the Fama–French model is able to explain the cross-section of equity returns. SMB and HML appear to contain other significant price information, unrelated to productivity. Our results show that productivity is a variable worth considering in asset-pricing tests, above and beyond size and book-to-market. Finally, using the Herfindahl index, we find that since 1990, firms in more competitive industries are more likely to show higher productivity and gain from it.

Figure 1

Annual Stock Returns and Productivity Growth in the Manufacturing Sector

This figure represents the value-weighted annual stock returns in the manufacturing sector and the capital stock-weighted productivity growth. The sample period is from July 1963 to December 2002. Value-weighted returns are constructed from July 1 in year t to June 30 in year $t+1$. Productivity growth is the rate of change in the 5-factor productivity level in the calendar year $t-1$ for 4-digit SIC industries.

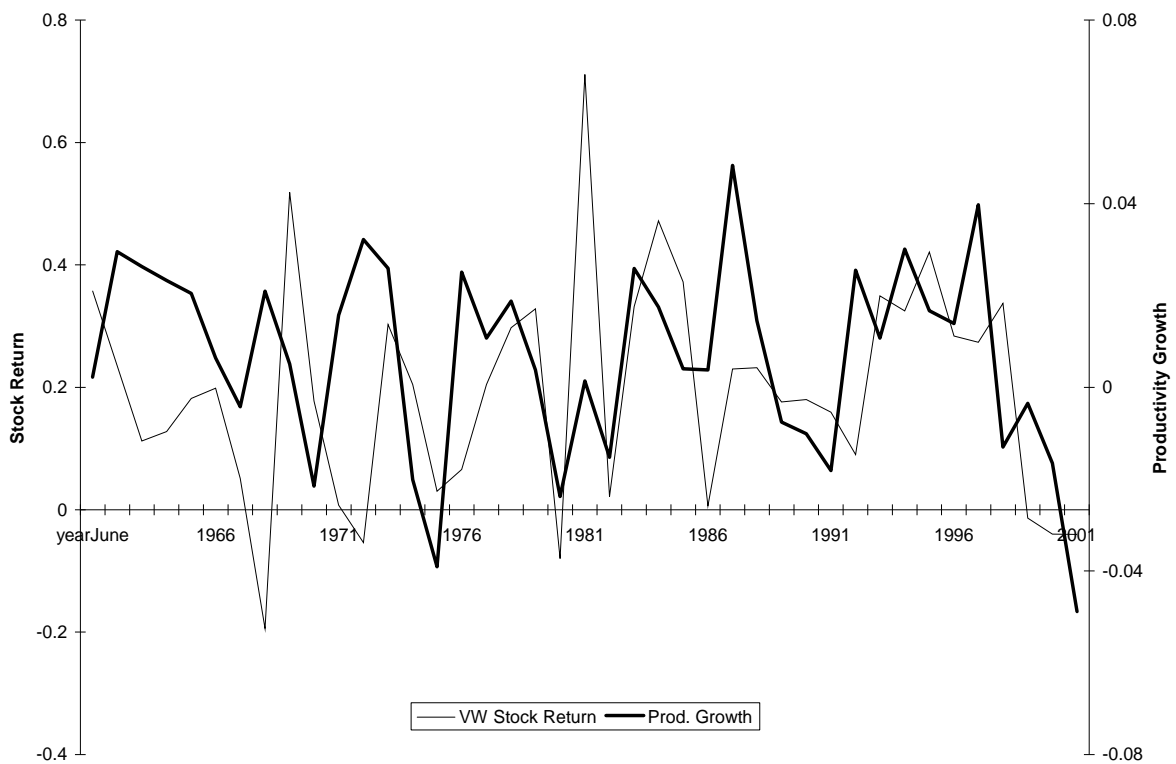


Figure 2

**Loadings on the Productivity Factor, PFSIC4Q
27 Size-B/M-Productivity Sorted Portfolios**

This figure plots the loadings or the coefficient estimates of the productivity factor. The four-factor orthogonal OLS regression model is:

$$R_t = \alpha + \beta_M * e_{R_{mt}} + \beta_{e_SMB} * e_{SMB_t} + \beta_{e_HML} * e_{HML_t} + \beta_{PF} * PFSIC4Q_t + e_t$$

where R_t is the equally-weighted monthly excess return of the test portfolio, R_{mt} is the monthly market excess return, $PFSIC4Q_t$ is the monthly productivity factor, $e_{R_{mt}}$, e_{SMB_t} and e_{HML_t} are the residuals from regressing R_{mt} , SMB , and HML on $PFSIC4Q_t$, respectively. The test portfolios are 27 size/Book-to-Market/productivity sorted manufacturing portfolios.

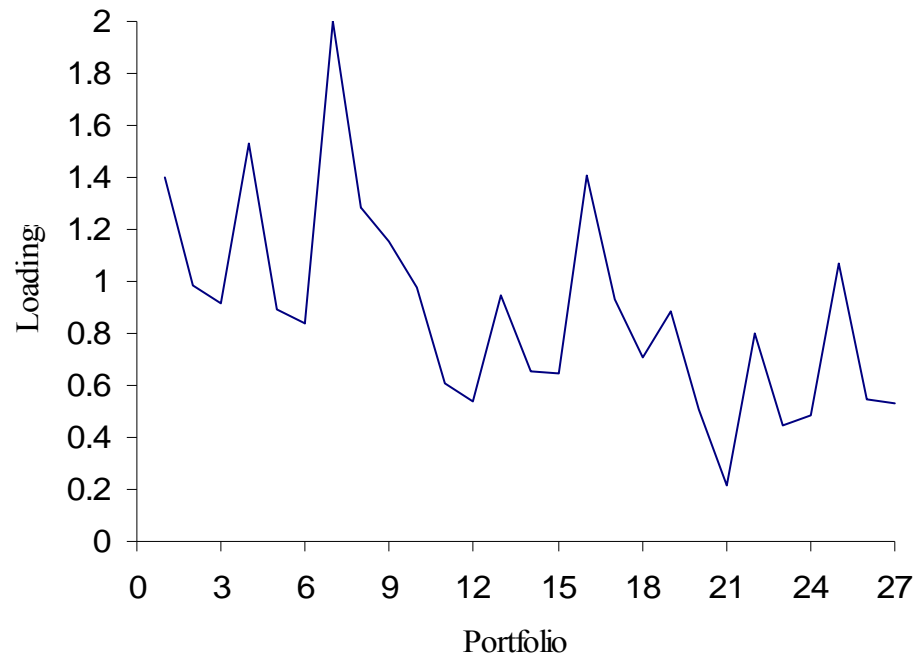


Table 1
Summary Statistics on the Manufacturing Sector, 1963-2002

This table reports the summary statistics for the manufacturing sector from July 1963 to December 2002. Panel A reports the number of industries per year and the average number of firms per industry per year. Panel B reports the weight of the manufacturing sector in the CRSP market portfolio. The CRSP market portfolio includes stocks from the NYSE, AMEX, and NASDAQ.

Panel A: Industry Classifications

Industry Classification	Number of Industries				
	Min	Q1	Median	Q3	Max
3-digit	96	120	122	125	129
4-digit	216	279	291	313	334
Industry Classification	Number of firms per industry				
	Min	Q1	Median	Q3	Max
3-digit	1	3	7	13	120
4-digit	1	1	3	5	88

Panel B: Relative Importance of the Manufacturing Sector: Snapshots

Year	Manufacturing as a Percentage of:	
	Total Number of Firms in CRSP (%)	Total Market Capitalization in CRSP (%)
1963	50	56
1983	26	42
2002	16	34

Table 2
Productivity, Stock Price, Size, B/M, and the Herfindahl Index
Manufacturing Sector, 1963-2002

Panel A presents the summary statistics for the capital-weighted average productivity, value-weighted stock price index, size, and B/M for each year. Panel B presents the correlation between each pair of variables. The productivity level is the annual 5-factor total productivity estimate from the NBER-CES Manufacturing Industry database. Both the productivity and the stock price level are normalized to one in 1963. Firm size is the market capitalization. The book-to-market ratio is book equity divided by market equity. The Herfindahl index is the sum of squared shares of each firm. The share of each firm is the market capitalization of the firm divided by the total capitalization of the industry. The higher the Herfindahl index, the less competition there is. Three asterisks (***) indicate statistical significance at 1 percent, two (**) indicate significance at 5 percent, and one (*) indicates significance at 10 percent.

Panel A: Annual Series

Year	Average Across All Manufacturing Industries				Correlation between Productivity Level and the Herfindahl index
	Productivity Level	Stock Price Index	Firm Size	Firm B/M	
1963	1.000	1.000	487,052	0.877	
1964	1.020	1.139	542,852	0.810	-0.092
1965	1.037	1.435	584,291	0.738	-0.037
1966	1.042	1.714	569,903	0.617	-0.067
1967	1.043	2.140	575,874	0.800	0.069
1968	1.055	2.121	599,318	0.569	0.067
1969	1.062	1.780	582,286	0.476	0.059
1970	1.041	2.321	454,258	0.778	0.067
1971	1.058	2.503	640,163	0.908	0.056
1972	1.092	2.232	716,377	0.818	0.023
1973	1.112	2.185	680,512	0.850	0.090
1974	1.099	2.422	530,735	1.399	0.054
1975	1.072	2.737	574,687	2.209	0.042
1976	1.097	2.890	629,688	1.588	-0.018
1977	1.124	3.172	582,832	1.257	0.029
1978	1.134	3.344	545,971	1.310	0.070
1979	1.141	3.475	575,010	1.321	0.072
1980	1.132	3.972	621,930	1.220	0.104*
1981	1.132	3.841	757,329	1.177	0.062
1982	1.130	4.855	665,758	1.239	0.092
1983	1.150	4.819	1,016,254	1.083	0.081
1984	1.179	5.079	941,903	0.810	0.082
1985	1.181	5.479	1,117,064	0.903	0.064
1986	1.129	5.742	1,659,008	0.779	-0.031

1987	1.225	5.785	2,114,305	0.763	0.064
1988	1.246	5.833	1,969,643	0.870	0.064
1989	1.300	5.854	2,153,287	0.804	0.085
1990	1.454	5.861	2,715,778	0.731	-0.067
1991	1.461	6.048	3,006,632	1.059	-0.039
1992	1.526	6.198	3,303,167	0.790	-0.055
1993	1.552	6.247	3,537,221	0.639	-0.105*
1994	1.615	6.434	3,512,604	0.555	-0.034
1995	1.721	6.675	4,484,065	0.614	-0.067
1996	1.830	6.851	5,418,070	0.573	-0.123**
1997	2.013	6.892	7,345,215	0.554	-0.134**
1998	2.054	6.921	8,703,010	0.508	-0.118*
1999	2.091	6.899	9,721,607	0.627	-0.071
2000	2.082	7.089	12,276,221	0.679	-0.111*
2001	1.924	7.133	9,982,521	0.925	-0.098
2002	1.987	6.970	8,419,403	0.806	-0.112**

Panel B: Correlation Matrix

	Productivity Level	Stock Price Index	Firm B/M	Firm Size
Productivity Level	1	0.831	-0.409	0.960
Stock Price Index		1	-0.294	0.750
Firm B/M			1	-0.384
Firm Size				1

Table 3
Productivity Factor-mimicking Portfolios, 1963-2002

This table presents the annualized percentage returns of several alternative specifications of the productivity factor-mimicking portfolios. PFSIC4D is the productivity factor formed on SIC 4-digit productivity deciles (top decile minus bottom decile equally-weighted portfolios). PFSIC3Q is the productivity factor formed on SIC 3-digit productivity quintiles (top quintile minus bottom quintile equally-weighted portfolios). The other productivity factors are similarly defined. SMB and HML are the Fama and French size and value factors. SMB_M and HML_M are the size and value factors constructed using the Fama and French methodology for the manufacturing sector. VW refers to value-weighted returns.

Productivity Factor	Annualized(%)		Correlation with SMB	Correlation with HML
	Mean	Median		
PFSIC4D EW	1.62	-0.52	0.3473	-0.4469
PFSIC4Q EW	0.95	0.18	0.3107	-0.3643
PFSIC3D EW	0.75	1.54	0.2439	-0.4543
PFSIC3Q EW	1.56	2.72	0.1841	-0.3581
PFSIC4D VW	2.41	0.49	0.2264	-0.4876
PFSIC4Q VW	1.77	1.35	0.1947	-0.4089
PFSIC3D VW	2.26	2.01	0.0019	-0.4762
PFSIC3Q VW	1.65	2.19	-0.1260	-0.3868
SMB_M	1.94	-0.25	0.9370	
HML_M	4.22	3.92		0.7280
SMB	2.69	1.09		
HML	5.31	5.54		

Table 4
CAPM-based Time-Series Regressions

This table reports the OLS coefficient estimates of the two-factor orthogonal model:

$$R_t = \alpha + \beta_M * e_{-R_{mt}} + \beta_{PF} * PFSIC4Q_t + \varepsilon_t$$

where R_t is the equally-weighted monthly excess returns of the test portfolio, $PFSIC4Q_t$ is the monthly productivity factor, and $e_{-R_{mt}}$ is the residual from regressing the monthly excess market return on $PFSIC4Q_t$. The test portfolios are constructed with firms in the manufacturing sector. Panel A uses 10 portfolios sorted by size, Panel B uses 10 portfolios sorted by B/M, and Panel C uses 25 portfolios independently sorted by size and B/M. Three asterisks (***) indicate statistical significance at 1 percent, two (**) indicate significance at 5 percent, and one (*) indicates significance at 10 percent.

Panel A: Portfolios Formed on Size Deciles

Portfolio from Small to Big	Mean Excess Return	Beta Coefficient Estimates			
		Two-Factor Orthogonal Model			
		<i>PFSIC4Q</i>	t-stat	<i>e_{-R_{mt}}</i>	t-stat
1	0.010	1.305***	21.92	0.910***	28.04
2	0.007	1.109***	25.65	1.055***	44.77
3	0.006	0.955***	21.54	1.106***	45.77
4	0.006	0.922***	22.42	1.104***	49.22
5	0.007	0.843***	20.10	1.124***	49.14
6	0.006	0.816***	18.89	1.127***	47.88
7	0.006	0.745***	16.85	1.162***	48.18
8	0.005	0.755***	17.22	1.177***	49.26
9	0.006	0.604***	16.51	1.097***	54.98
10	0.005	0.566***	21.06	1.013***	69.12

The correlation coefficient between mean excess returns and the beta of *PFSIC4Q* is 0.839.

Panel B: Portfolios formed on B/M Deciles

Portfolio from Small to Big	Mean Excess Return	Beta Coefficient Estimates			
		Two-Factor Orthogonal Model			
		<i>PFSIC4Q</i>	t-stat	<i>e_{-R_{mt}}</i>	t-stat
1	0.002	1.200***	19.69	1.178***	38.17
2	0.004	1.037***	18.83	1.134***	40.68
3	0.007	0.969***	16.04	1.118***	36.54
4	0.006	0.908***	13.81	1.086***	32.62
5	0.008	0.920***	14.14	1.054***	31.99
6	0.008	0.817***	12.14	1.055***	30.98
7	0.010	0.889***	12.38	1.016***	27.96
8	0.010	0.894***	12.00	1.017***	26.97
9	0.011	0.948***	11.72	0.989***	24.16
10	0.013	1.042***	10.95	0.939***	19.49

The correlation coefficient between mean excess returns and the beta of *PFSIC4Q* is -0.497.

Panel C: Portfolios Formed on Size and B/M Quintiles

Size from Small to Big	B/M from Low to High	Mean Excess Return	Beta Coefficient Estimates			
			Two-Factor Orthogonal Model			
			<i>PFSIC4Q</i>	t-stat	<i>e_R_{mt}</i>	t-stat
1	1	0.002	1.701***	14.14	1.180***	19.37
	2	0.007	1.404***	13.06	1.059***	19.46
	3	0.009	1.151***	12.16	1.016***	21.22
	4	0.011	1.151***	12.08	0.958***	19.86
	5	0.013	1.146***	11.73	0.904***	18.27
2	1	0.000	1.487***	15.73	1.302***	27.19
	2	0.007	0.947***	11.83	1.150***	28.37
	3	0.007	0.776***	10.35	1.039***	27.36
	4	0.009	0.772***	10.19	1.080***	28.15
	5	0.009	0.703***	7.66	1.106***	23.83
3	1	0.004	1.071***	14.33	1.200***	31.70
	2	0.006	0.869***	12.64	1.109***	31.87
	3	0.007	0.777***	11.38	1.125***	32.54
	4	0.009	0.608***	8.95	1.045***	30.37
	5	0.008	0.623***	7.17	1.115***	25.34
4	1	0.004	0.931***	15.71	1.128***	37.59
	2	0.005	0.743***	12.90	1.150***	39.45
	3	0.008	0.664***	11.30	1.104***	37.09
	4	0.008	0.610***	8.32	1.147***	30.93
	5	0.008	0.744***	8.14	1.162***	25.10
5	1	0.005	0.719***	16.07	0.986***	43.49
	2	0.006	0.554***	12.67	1.017***	45.98
	3	0.006	0.452***	8.48	1.021***	37.77
	4	0.008	0.376***	6.05	1.010***	32.15
	5	0.008	0.429***	3.59	1.012***	16.73

We report below the results from the following model, in which we regress the excess market return on the productivity factor. There are 474 monthly observations. The residuals from this model, $e_{R_{mt}}$, are used in the regressions above.

$$R_{mt} = \alpha + \beta_{PF} \times PFSIC4Q_t + e_t$$

Intercept	t-stat	Beta coefficient	t-stat	Adjusted R ²	F
0.0035*	1.80	0.7095***	7.80	0.1124	60.90

Table 5
Fama and French-based Time-Series Regressions

We report below the results from the following two models, in which we regress SMB_t and HML_t on the productivity factor, respectively. There 474 monthly observations. The residuals from the models, e_SMB_t and e_HML_t , are used in the regressions below.

$$SMB_t = \alpha + \beta_{PF} \times PFSIC4Q_t + e_t$$

Intercept	t-stat	Beta coefficient	t-stat	Adjusted R ²	F
0.0018	1.28	0.4761***	7.10	0.0946	50.43

$$HML_t = \alpha + \beta_{PF} \times PFSIC4Q_t + e_t$$

Intercept	t-stat	Beta coefficient	t-stat	Adjusted R ²	F
0.0047***	3.67	-0.5085***	-8.50	0.1309	72.22

Panels A to C below report the OLS coefficient estimates of the four-factor orthogonal model:

$$R_t = \alpha + \beta_m * e_R_{mt} + \beta_{SMB} * e_SMB_t + \beta_{HML} * e_HML_t + \beta_{PF} * PFSIC4Q_t + \varepsilon_t$$

where R_t is the equally-weighted monthly excess returns of the test portfolio, $PFSIC4Q_t$ is the monthly productivity factor, e_R_{mt} , e_SMB_t and e_HML_t are the residuals from regressing the monthly excess market return, SMB_t and HML_t , on $PFSIC4Q_t$, respectively. The test portfolios are constructed with firms in the manufacturing sector. Panel A uses 10 portfolios sorted by size, Panel B uses 10 portfolios sorted by B/M, and Panel C uses 25 portfolios independently sorted by size and B/M. Three asterisks (***) indicate statistical significance at 1 percent, two (**) indicate significance at 5 percent, and one (*) indicates significance at 10 percent.

Panel A: Portfolios Formed on Size Deciles

Portfolio From Small to Big	Mean Excess Return	Beta Coefficient Estimates							
		Four-Factor Orthogonal Model							
		<i>PFSIC4Q</i>	t-stat	$e_{R_{mt}}$	t-stat	e_{SMB}	t-stat	e_{HML}	t-stat
1	0.010	1.305***	21.92	0.910***	28.04	1.215***	28.85	0.555***	11.29
2	0.007	1.109***	25.65	1.055***	44.77	0.951***	31.08	0.444***	12.43
3	0.006	0.955***	21.54	1.106***	45.77	0.864***	27.54	0.391***	10.68
4	0.006	0.922***	22.42	1.104***	49.22	0.827***	28.41	0.413***	12.15
5	0.007	0.843***	20.10	1.124***	49.14	0.671***	22.60	0.404***	11.66
6	0.006	0.816***	18.89	1.127***	47.88	0.521***	17.04	0.358***	10.05
7	0.006	0.745***	16.85	1.162***	48.18	0.332***	10.61	0.275***	7.54
8	0.005	0.755***	17.22	1.177***	49.26	0.181***	5.82	0.338***	9.33
9	0.006	0.604***	16.51	1.097***	54.98	-0.014	-0.54	0.183***	6.06
10	0.005	0.566***	21.06	1.013***	69.12	-0.275***	-14.43	0.026	1.18

The correlation coefficient between mean excess returns and the beta of *PFSIC4Q* is 0.839.

Panel B: Portfolios Formed on B/M Deciles

Portfolio From Low to High	Mean Excess Return	Beta Coefficient Estimates							
		Four-Factor Orthogonal Model							
		<i>PFSIC4Q</i>	t-stat	$e_{R_{mt}}$	t-stat	e_{SMB}	t-stat	e_{HML}	t-stat
1	0.002	1.200***	24.50	1.066***	39.92	0.525***	15.14	0.144***	-3.55
2	0.004	1.037***	23.84	1.068***	45.02	0.520***	16.89	0.055	1.52
3	0.007	0.969***	22.89	1.094***	47.39	0.635***	21.21	0.320***	9.14
4	0.006	0.908***	20.49	1.074***	44.43	0.699***	22.28	0.415***	11.33
5	0.008	0.920***	20.77	1.056***	43.73	0.665***	21.22	0.458***	12.53
6	0.008	0.817***	18.80	1.083***	45.74	0.675***	21.97	0.578***	16.12
7	0.010	0.889***	22.69	1.025***	47.96	0.831***	29.96	0.597***	18.45
8	0.010	0.894***	21.76	1.027***	45.87	0.856***	29.43	0.622***	18.35
9	0.011	0.948***	21.25	1.014***	41.68	0.908***	28.75	0.720***	19.53
10	0.013	1.042***	18.71	0.962***	31.69	1.047***	26.56	0.808***	17.57

The correlation coefficient between mean excess returns and the beta of *PFSIC4Q* is -0.497.

Panel C: Portfolios Formed on Size and B/M Quintiles

Size from Small to Big	B/M from Low to High	Mean Excess Return	Beta Coefficient Estimates							
			Four-Factor Orthogonal Model							
			<i>PFSIC4Q</i>	t-stat	<i>e_R_{mt}</i>	t-stat	<i>e_SMB</i>	t-stat	<i>e_HML</i>	t-stat
1	1	0.002	1.701***	21.49	0.977***	22.63	1.385***	24.72	0.032	0.50
	2	0.007	1.404***	19.80	0.961***	24.85	1.231***	24.53	0.392***	6.70
	3	0.009	1.151***	18.83	0.975***	29.27	1.063***	24.58	0.534***	10.58
	4	0.011	1.151***	22.03	0.919***	32.25	1.166***	31.53	0.612***	14.18
	5	0.013	1.146***	20.07	0.903***	29.01	1.113***	27.56	0.746***	15.84
2	1	0.000	1.487***	20.42	1.133***	28.55	0.897***	17.41	-0.143**	-2.37
	2	0.007	0.947***	18.03	1.063***	37.14	0.926***	24.92	0.238***	5.49
	3	0.007	0.776***	13.83	1.036***	33.88	0.703***	17.71	0.461***	9.95
	4	0.009	0.772***	15.70	1.078***	40.19	0.813***	23.35	0.536***	13.20
	5	0.009	0.703***	11.86	1.144***	35.44	0.920***	21.95	0.789***	16.12
3	1	0.004	1.071***	16.44	1.127***	31.72	0.566***	12.28	0.057	1.05
	2	0.006	0.869***	15.64	1.087***	35.89	0.595***	15.14	0.306***	6.67
	3	0.007	0.777***	14.57	1.152***	39.63	0.553***	14.65	0.495***	11.23
	4	0.009	0.608***	12.56	1.095***	41.49	0.578***	16.87	0.612***	15.30
	5	0.008	0.623***	9.24	1.178***	32.04	0.655***	13.72	0.720***	12.92
4	1	0.004	0.931***	16.62	1.057***	34.60	0.259***	6.53	-0.141***	-3.05
	2	0.005	0.743***	14.28	1.191***	41.98	0.265***	7.20	0.360***	8.37
	3	0.008	0.664***	12.89	1.160***	41.28	0.275***	7.53	0.435***	10.22
	4	0.008	0.610***	9.73	1.253***	36.71	0.260***	5.86	0.648***	12.53
	5	0.008	0.744***	9.36	1.262***	29.12	0.405***	7.19	0.720***	10.96
5	1	0.005	0.719***	17.70	0.977***	44.10	-0.252***	-8.76	-0.208***	-6.20
	2	0.006	0.554***	13.13	1.068***	46.45	-0.064**	-2.13	0.184***	5.29
	3	0.006	0.452***	9.29	1.115***	42.00	-0.066*	-1.93	0.375***	9.32
	4	0.008	0.376***	6.82	1.132***	37.69	-0.064	-1.63	0.497***	10.93
	5	0.008	0.429***	4.29	1.259***	23.08	0.118*	1.66	1.176***	14.23

Table 6
Summary Statistics
27 Size/Book-to-Market/Productivity Sorted Portfolios

This table shows the average excess returns on 27 size/Book-to-Market/productivity sorted manufacturing portfolios. A three-way independent sorting was performed based on size, B/M, and 4-digit SIC tfp5 productivity. Stocks in deciles 1-3 are categorized into the top group, stocks in decile 4-6 are categorized into the middle group, and stocks in decile 7-10 are categorized into the bottom group. The intersection of the three-way independent sorting gives 27 portfolios.

Portfolio	Size	B/M	Productivity	Mean Excess Return (%)
1	S	H	H	1.24
2	S	H	M	1.23
3	S	H	L	1.17
4	S	M	H	0.99
5	S	M	M	0.76
6	S	M	L	0.94
7	S	L	H	0.49
8	S	L	M	0.47
9	S	L	L	0.28
10	M	H	H	0.98
11	M	H	M	0.75
12	M	H	L	0.80
13	M	M	H	0.85
14	M	M	M	0.83
15	M	M	L	0.64
16	M	L	H	0.36
17	M	L	M	0.48
18	M	L	L	0.41
19	B	H	H	0.78
20	B	H	M	0.66
21	B	H	L	0.94
22	B	M	H	0.67
23	B	M	M	0.64
24	B	M	L	0.60
25	B	L	H	0.51
26	B	L	M	0.46
27	B	L	L	0.53

Table 7
Asset Pricing Tests on 27 Size/Book-to-Market/Productivity Sorted Portfolios

This table reports the results of the asset pricing tests using 27 size/Book-to-Market/productivity sorted manufacturing portfolios. Panels A and B show the results from the SDF approach: Panel A for the estimates of the pricing coefficients, b , and Panel B for the risk premiums, λ . Panel C shows the estimates of the risk premiums from the two-step cross-sectional GLS regression approach. M is the equally-weighted monthly excess portfolio return. Data for M, SMB and HML are obtained from Kent French's website. PFSIC4Q_t is the monthly productivity factor, and e_M, e_SMB, and e_HML are the residual from regressing M, SMB, and HML on PFSIC4Q_t, respectively. Three asterisks (***) indicate statistical significance at 1 percent, two (**) indicate significance at 5 percent, and one (*) indicates significance at 10 percent.

Panel A: pricing coefficient estimates from the SDF approach

	CAPM		Fama-French		Model 3		Model 4	
	b	t-stat	b	t-stat	b	t-stat	b	t-stat
PFSIC4Q					9.1439**	2.06	5.9047	1.63
M	2.3540**	2.10	4.7889***	3.32	4.2254***	2.80		
SMB			1.0854	0.62	-0.3603	-0.18		
HML			9.7195***	4.12	11.9289***	4.61		
e_M							4.2254***	2.80
e_SMB							-0.3603	-0.18
e_HML							11.9289***	4.61
mHJ distance	0.4195		0.3641		0.3506		0.3506	
p-value	0.0000		0.0000		0.0010		0.0010	

Panel B: risk premium estimates from the SDF approach

	CAPM		Fama-French		Model 3		Model 4	
	λ	t-stat	λ	t-stat	λ	t-stat	λ	t-stat
PFSIC4Q					0.002	1.63	0.0027	1.63
M	0.0048**	2.10	0.0046*	1.89	0.0046*	1.82		
SMB			0.0005	0.28	0.0001	0.06		
HML			0.0057***	3.03	0.0063***	3.15		
e_M							0.0027	1.04
e_SMB							-0.0012	-0.60
e_HML							0.0077***	3.89

Panel C: risk premium estimates from the two-step cross-sectional GLS regression approach

	CAPM			Fama-French			Model 3			Model 4		
	λ	t-stat	Shanken's t	λ	t-stat	Shanken's t	λ	t-stat	Shanken's t	λ	t-stat	Shanken's t
PFSIC4Q							0.0027*	1.73	1.67	0.0027*	1.73	1.67
M	0.0048**	2.22	2.22	0.0046**	2.15	2.15	0.0046**	2.14	2.13			
SMB				0.0005	0.32	0.32	0.0001	0.07	0.07			
HML				0.0057***	3.37	3.32	0.0063***	3.66	3.58			
e_M										0.0027	1.21	1.19
e_SMB										-0.0012	-0.68	-0.67
e_HML										0.0077***	4.24	4.12
csrt		0.1740			0.1230			0.1098			0.1098	
p-value		0.0000			0.0003			0.0012			0.0012	

Table 8

OLS Estimation on the Pooled 20 2-Digit SIC Industry Portfolios

This table reports the pooled OLS regression results on 20 2-digit SIC industries from July 1963 to December 2002. Panel A reports the results from July 1963 to December 1989. Panel B reports the results from January 1990 to December 2002. $PFSIC4Q_t$ is the monthly productivity factor, and e_M_t , e_SMB_t , and e_HML_t are the residuals from regressing M , SMB , and HML on $PFSIC4Q_t$, respectively. The Herfindahl index is the sum of squared shares of each firm in the industry. The share of each firm is the market capitalization of the firm divided by the total capitalization of the industry. Three asterisks (***) indicate statistical significance at 1 percent, two (**) indicate significance at 5 percent, and one (*) indicates significance at 10 percent.

Panel A: July 1963 - December 1989

	Model 1		Model 2		Model 3	
	Coefficient estimate	t-stat	Coefficient estimate	t-stat	Coefficient estimate	t-stat
Constant	0.007***	17.67	0.007***	17.05	0.007***	17.68
e_M	0.974***	101.63	0.979***	96.58	0.974***	101.61
e_SMB	0.968***	66.85	0.973***	63.43	0.968***	66.81
e_HML	0.291***	18.62	0.346***	21.07	0.292***	18.64
PFSIC4Q	1.067***	49.55			1.031***	27.63
PFSIC4Q*Herfindahl			5.233***	38.88	0.257	1.17
F	6226		5389		4981	
adj R ²	0.797		0.772		0.797	

Panel B: January 1990 - December 2002

	Model 1		Model 2		Model 3	
	Coefficient estimate	t-stat	Coefficient estimate	t-stat	Coefficient estimate	t-stat
Constant	0.006***	8.10	0.007***	8.42	0.006***	8.04
e_M	1.017***	47.38	0.977***	42.91	1.019***	47.70
e_SMB	0.580***	25.60	0.533***	22.17	0.579***	25.66
e_HML	0.693***	22.95	0.590***	18.54	0.689***	22.92
PFSIC4Q	0.775***	26.07			0.952***	21.32
PFSIC4Q*Herfindahl			1.967***	15.04	-0.976***	-5.29
F	763		579		621	
adj R ²	0.494		0.426		0.499	

References

- Balvers, R., and D. Huang, 2007. Productivity-based asset pricing: theory and evidence. *Journal of Financial Economics* 86, 405-445.
- Bartelsman, E., and W. Gray, 1996. The NBER manufacturing productivity database. *NBER working paper* 205.
- Black, F., M. Jensen and M. Scholes, 1972. The capital asset pricing model: some empirical tests. *Studies in the Theory of Capital Markets*, Praeger.
- Breeden, D, 1979. An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics* 7, 265–296.
- Breeden, M., R. Gibbons, and R. Litzenberger, 1989. Empirical tests of the consumption-oriented CAPM. *Journal of Finance* 44. 231-262.
- Campbell, J. and J. Cochrane, 1999. By force of habit: a consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy* 107, 205-251.
- Campbell, J. and J. Cochrane, 2000. Explaining the poor performance of consumption-based asset pricing models. *Journal of Finance* 55, 2863-2878.
- Chamberlin, G., S. Hall and M. Satchi, 2002. Productivity trends, asset returns and rebalancing the U.S. economy. Working paper, Oxford University.
- Chen, N., R Roll, and S A. Ross, 1986. Economic forces and the stock market. *Journal of Business* 56, 383-403.
- Cochrane, J., 1991. Production-based asset pricing and the link between stock returns and economic fluctuation. *Journal of Finance* 46, 208-237.
- Cochrane, J., 2001. Asset pricing. Princeton University Press.

- Dittmar, R. F., 2002. Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. *Journal of Finance* 57, 369-403.
- Epstein, L., and S. Zin, 1989. Substitution, Risk aversion and the temporal behavior of consumption and asset returns: a theoretical framework. *Econometrica* 57, 937-969.
- Fama, E and K. R French, 1992. The cross section of expected stock returns. *Journal of Finance* 59, 427-465.
- Fama, E. F., and K. R. French, 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.
- Farnsworth, H., W. E. Ferson, D. Jackson, and S. Todd, 2002. Performance evaluation with stochastic discount factors. *Journal of Business* 75, 473-503.
- Harvey, C.R., 1989. Time varying conditional covariances in tests of asset pricing models. *Journal of Financial Economics* 24, 289-317.
- Harvey, C. R., and A. Siddique, 2000. Conditional skewness in asset pricing tests. *Journal of Finance* 55, 1263-1296.
- Hansen, L. P., and R. Jagannathan, 1997. Assessing specification errors in stochastic discount factor models. *Journal of Finance* 52, 557-590.
- Hirshleifer, J., 1958. On the theory of optimal investment decisions. *Journal of Political Economy* 66, 329-352.
- Hodrick, R. J., and X. Zhang, 2001. Evaluating the specification errors of asset pricing models. *Journal of Financial Economics* 62, 327-376.

- Hou, Kewei and David T. Robinson, 2006, Industry Concentration and Average Stock Returns. *Journal of Finance* LXI, 4, 1927-1956.
- Jagannathan, R., K. Kubota, and H. Takehara, 1998. Relationship between labor-income risk and average return: empirical evidence from the Japanese stock market. *Journal of Business* 71, 319-348.
- Jagannathan, R., and Z. Wang, 1996. The conditional CAPM and the cross-section of expected returns. *Journal of Finance* 51, 3-53.
- Jagannathan, R., and Z. Wang, 2002. Empirical evaluation of asset pricing models: a comparison of the SDF and beta methods. *Journal of Finance*, 57, 2337-2367.
- Jagannathan, R., and Y. Wang, 2007. Lazy investors, discretionary consumption, and the cross section of stock returns. *Journal of Finance* 62, 1623-1661.
- Kan, R., and C. Robotti, 2008. Specification tests of asset pricing models using excess returns. *Journal of Empirical Finance*, forthcoming.
- Kan, R., and G. Zhou, 1999. A critique of the stochastic discount factor methodology. *Journal of Finance* 54, 1221-1248.
- Kan, R., and G. Zhou, 2001. Empirical asset pricing: the beta method versus the stochastic discount factor method. working paper, University of Toronto and Washington University in St. Louis.
- Kandall, S., and R. Stambaugh, 1990. Expectations and volatility in consumption and asset returns. *Review of Financial Studies* 3, 207-232.
- Lehmann, B., and D. M. Modest, 1988. The empirical foundations of the arbitrage pricing theory. *Journal of Financial Economics* 21, 213-254.

- Lettau, M., and S. Ludvigson, 2001. Resurrecting the (C) CAPM: a cross-sectional test when risk premia are time-varying. *Journal of Political Economy* 109, 1238-1287.
- J. Lintner, 1965. Security prices, risk and the maximal gains from diversification. *Journal of Finance* 20, 587-616.
- R. Lucas, 1978. Asset prices in an exchange economy. *Econometrica* 46, 1429-1445.
- Mankiw, G., and Matthew Shapiro, 1986. Risk and return: consumption versus market beta. *Review of Economics and Statistics* 68, 452-459.
- Mark, J.A., 1982. Measuring productivity in service industries. *Monthly Labor Review online* 105.
- Marshall, D., and Nayan G. Parekh, 1999. Can costs of consumption adjustment explain asset pricing puzzles? *Journal of Finance* 54, 623-654.
- Massa , Massimo, Zahid Rehman and Theo Vermaelen, 2007. Mimicking repurchases. *Journal of Financial Economics* 84, 3, 624-666.
- Merton, R., 1973 An inter-temporal capital asset pricing model. *Econometrica* 41, 867-887.
- Ramsey, R., 1928. A mathematical theory of saving. *Economic Journal* 38, 543-559.
- Rubinstein, M., 1976. The Valuation of uncertain income streams and the pricing of options. *Bell Journal of Economics and Management Science* 7, 407-425.
- Shanken, J., 1985. Multivariate tests of the zero-beta CAPM. *Journal of Financial Economics* 14, 327-348.
- W. Sharpe, 1964. Capital asset prices: a theory of market equilibrium under conditions of uncertainty. *Journal of Finance* 19, 452-442.
- Shumpeter, J., 1942. Capitalism, socialism and democracy. Harper.

Stapleton, R., and M. Subrahmanyam, 1978. A multi-period equilibrium asset-pricing model. *Econometrica* 46, 1077-1096.

Von Neumann, J., 1945. A model of general economic equilibrium. *Review of Economic Studies* 13, 1-9

Wheatley, S., 1988. Some tests of the consumption-based asset pricing model. *Journal of Monetary Economics* 22, 193-215.

ⁱ See Black, Jensen and Scholes (1972) for the first modern test of the CAPM.

ⁱⁱ See Jaganathan et al. (2008) for a summary of recent evidence for the CCAPM.

ⁱⁱⁱ Capital gains and losses are not included in the GNP accounts since in aggregate the economy like the representative agent can not consume capital gains and losses.

^{iv} Current Analysis, RBC Financial Group, October 2006 available at rbc.com/economics.

^v The first-order condition is increasingly referred to as the “pricing kernel” and γ the stochastic discount factor.

^{vi} The Bureau of Labour Statistics (BLS) provides multi-factor productivity estimates for 3-digit SIC industries from 1987 to 1999. We aggregate capital-weighted tfp for the whole manufacturing sector and find that the correlation between the NBER-CES measure and the BLS measure is 0.90 from 1987 to 1999. Since NBER-CES provides finer data at the 4-digit SIC industry level and covers a much longer time period, we use their measure.

^{vii} The NBER-CES productivity data covers all firms in each industry, but the stock return data covers only publicly-traded data. A natural question to ask is how this difference may influence our results? We do not know how the productivity of publicly-traded firms is different than that of non-traded private firms. Nevertheless, even if there is a difference, there is really no way to get around this limitation.

^{viii} The correlation between these two series is 0.24 for the whole sample period, but 0.54 after 1982.

^{ix} The Herfindahl index is superior to the concentration ratio because concentration ratios ignore the number of firms in the industry overall. For example, imagine two industries with the same four-firm concentration ratios, but one with only 10 firms and the other with 1,000 firms. The Herfindahl index takes these differences into account, whereas the concentration ratios do not.

^x For a detailed discussion, see Mark (1982).

^{xi} It is worth highlighting that we are dealing with an unbalanced panel, with firms entering and exiting the sample over time. We do not believe this has a significant impact on our results. First of all, we only consider the average returns in the top and bottom quintiles. The entrance and exit of firms in the middle quintiles do not matter. Second, even for the top and bottom quintiles, we only use the difference of average return instead of each firm’s information. Instead, the ignorance of the entrance and exit may underestimate the productivity premium. High-productivity industries attract new incomers which may have less productivity than the current firms and drag down the return in the next year. Also when the least productive firms exit low-productivity industries, the staying firms on average have higher productivity and higher expected return than the existed firms in the same industry

^{xii} This approach is the most widely used asset pricing test. See for example, Fama and French (1992), Harvey and Siddique (2000), Lettau and Ludvigson (2001), and Li,

Vassalou, and Xing (2004), among others. For a discussion of this approach, see Chen, Roll, and Ross (1986), Shanken (1992), Jagannathan and Wang (1997), Ferson and Harvey (1993), and Kan and Zhang (1999).

^{xiii} This method is equivalent to Fama and MacBeth (1973) if the errors are uncorrelated over time, which may not be an unreasonable assumption since returns are fairly independent.

^{xiv} We test these four models on 25 equally-weighted size/BM portfolios for the whole NYSE/AMEX/NASDAQ database which are obtained from Kent French's website. The test results are similar to table 7.