December 16, 2008

The Influence of Productivity on Asset Pricing

Laurence Booth, Bin Chang, Walid Hejazi, and Pauline Shum*

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 4-digit industry-level total factor productivity estimates. This factor captures the difference in stock returns between high and low productivity industries. Between 1963 and 2002, the productivity premium contributes on average 0.75 to 2.41 percent per annum for the range of productivity factors we construct. Our results show that i) in accordance with our hypothesis, productivity has a robust, positive impact on returns, and this impact is bigger on smaller, growth firms, and ii) productivity helps price assets even when size, book-to-market, and momentum are taken into account. Finally, since 1990, firms in more competitive industries are more likely to show higher productivity and gain from it.

JEL classification: G12
Keywords: Productivity, asset pricing, Fama and French factors

* Bin Chang is from the Faculty of Business & IT at the University of Ontario Institute of Technology, Laurence Booth and Walid Hejazi are from the Rotman School of Management at the University of Toronto. Pauline Shum is from the Schulich School of Business at York University. We thank Wayne Gray and Debarshi Nandy for providing the productivity data, Raymond Kan, Dan Trefler, and participants at the 2008 Northern Finance Association Conference, the Rotman Doctoral Student Finance Seminar, and the Schulich Finance Brown-Bag seminar for valuable comments.

I. Introduction

In this paper, we examine the link between productivity and the cross-section of stock returns. Productivity plays an important role in modern theories of economic growth, dating back to classic works by Ramsey (1928) and Schumpeter (1934). Ceteris Paribus, highly productive economies translate to high economic growth and high expected rates of return. Although the early models did not deal with uncertainty, the intuition would then follow that uncertainty surrounding the rate of productivity and economic growth should be a primary factor in pricing risky assets.

Our focus on the production side of the economy is in part motivated by the poor empirical performance of the consumption-based CAPM (CCAPM), which, while intuitively appealing, has yet to receive convincing empirical validation. On the other hand, the empirical weakness of the original CAPM of Sharpe (1964) and Lintner (1965) has given rise to the Fama-French (1992, 1993) three-factor model. Although factors such as size and book-to-market help explain a significant part of the cross-sectional variation in stock returns, it is still not clear whether these firm characteristics reflect risk differences or market imperfections. Our hypothesis is that productivity is related to both size and book-to-market, thereby providing some economic intuition for these two celebrated factors. As a robustness check, we also consider the impact of momentum as an additional factor, although the link between momentum risk and productivity is not obvious (in fact, the correlation between the two is -0.085).

First, with respect to size, Schumpeter recognized the "creative destructive" forces of capitalism generated by productivity and/or technological change. These forces primarily affect young firms as new industries are created and old ones die. Chamberlin et al. (2002) look at how productivity changes affect the stock market during the Internet Bubble, which was largely driven by young start-ups. RBC Financial Group also notes in a research report[1] that, "… (in) 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." Hence, productivity should be negatively related to size. Second, with respect to book-to-market, 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. In addition, highly productive firms will experience high growth. Both observations translate to a lower book-to-market ratio.

Our line of research follows recent efforts to include additional state variables in the asset pricing model.[2] The idea that asset prices may be related to productivity has recently been examined by Balvers and Huang (2007). They show 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 intertemporal transformation. The latter is the rate of return on investment, as in the early certainty model of Hirshleifer (1958). Balvers and Huang implement this idea through the sensitivity of a security to a single aggregate productivity shock. While the results from their theoretical model are intuitively attractive, the empirical support is mixed.

In this paper, we contribute to the empirical evidence from a different perspective. We make use of disaggregate (four-digit SICs) productivity data for the manufacturing

[1] Current Analysis, RBC Financial Group, October 2006, available at: http:// rbc.com/economics.

[2] 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).

sector, provided by the National Bureau of Economic Research (NBER) and the U.S. Census Bureau's Centre for Economic Studies (CES). We follow the factor-mimicking portfolio technology introduced by Fama and French (1993), which has revolutionized the empirical asset pricing literature, 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).

By creating factor mimicking portfolios with respect to productivity, we capture the intuition that it is the stock market reaction to productivity changes, in creating uncertain capital gains and losses that causes risk, rather than the productivity changes themselves that influence returns. This is important since it is difficult to capture uncertain capital gains and losses in a representative agent economy[3], as in the case of Balvers and Huang.

In examining the impact of productivity differences across industries, we attempt to address three main research questions. First, do stock returns reflect productivity, a fundamental determinant of growth? Second, is productivity priced in the stock market? And third, are the well-known factors, namely, size and book-to-market related to productivity, thereby providing them with an economic interpretation as well as insight into why these firm characteristics may reflect risk factors?

To preview our results, we find that for the range of productivity factors we constructed, they contribute 0.75 to 2.41 percent annually. This is a similar order of magnitude to the Fama-French size premium, but less than the value premium. More

[3] Capital gains and losses are not included in the GNP accounts since in aggregate the economy, like the representative agent cannot consume capital gains and losses.

importantly, productivity has a positive impact on returns as we hypothesized, and it is shown to be a significant factor in pricing assets, even after we control for size, book-to-market, and momentum. We also find that the impact of productivity on firms is not universal. Instead, it has a higher impact on small and growth firms. Further, we show that book-to-market does explain priced information that is unrelated to productivity, and it is extremely robust.

Since our test assets are portfolios of manufacturing firms, our results also have implications for fund managers. Manufacturing, after all, accounts for more than 50 percent of the S&P500 companies in 2002. We find that size and momentum are not important factors for pricing assets in this sector.

The remainder of the paper is organized as follows. Section II discusses our model, data and summary statistics. Section III describes our asset pricing tests and results. Section IV extends the analysis to examine the impact of industry concentration on productivity and asset returns. Section V provides conclusions.

II. <u>The Model, Data, and Summary Statistics</u>

Theoretical asset pricing models are typically based on the first-order condition for a representative agent maximizing a von-Neumann–Morgenstern expected utility function. That is, for any security j,

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

where R_j is the return on the jth risky asset, and γ is the marginal rate of substitution between time periods 0 and 1.[4] Expanding the expectation and assuming approximate normality, Rubinstein (1976) showed that (1) can be reformulated as an asset pricing model,

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

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 in the utility function is uncertain wealth, then the marginal rate of substitution is determined by the market portfolio, as in the CAPM. If we define z as a linear function of various risks in the economy, we get a linear pricing model. For three factors, F_1, F_2, and F_3, we have,

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

This specification 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, 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 and Ramsey, the market return in a complete market is equal to

[4] The first-order condition is increasingly referred to as the "pricing kernel" and γ the stochastic discount factor.

the return on investment. The two or three additional risk factors can then be viewed as hedging portfolios in the spirit of Merton (1973), Stapleton and Subrahmanyam (1978), and Breeden (1979). One such hedging portfolio would be the return on a productivity factor which shifts the aggregate production function, and thus the return on investment.

In this paper, we will consider the following empirical specifications. First, we examine the empirical relevance of productivity and its impact on the overall stock market. Second, we consider the productivity factor within the context of the Fama-French three-factor model to see whether size and book-to-market proxy for the more primal productivity factor. Finally, we extend the empirical model to include the well-documented momentum factor.

Our productivity data come from the NBER-CES 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. We use the five-factor productivity estimate as our measure of productivity, where the five factors are: Capital, production worker, non-production workers, energy, and non-energy material. *TFP* reflects output per unit of a set of combined inputs. A change in *TFP* reflects the change in output that cannot be accounted for by the change in that set of combined inputs. Consequently, *TFP* represents the joint effects of many forces, such as research and development, technological break-through, economies of scale, managerial skill, and changes in the organization of production.

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. *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.

There is an active research agenda as to the correct deflator to calculate the real growth rates.[5] However, this does not seem to be significant for the resulting *TFP* measure. For example, 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 for 1987-1999 the correlation between the NBER-CES measure and the BLS measure is 0.90. Since the NBER-CES measure provides finer data at the 4-digit SIC industry level and covers a much longer time period, we use this estimate in our tests.

The productivity dataset covers 459 4-digit SIC manufacturing industries from 1958 to 2002.[6] Our stock market data are from CRSP. Although the productivity data start in 1958, merging the two datasets leaves only one industry in the manufacturing sector for the first four years (1958 to 1962). Hence, our empirical analysis begins in

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[5] See Young (1995)

[6] Firm-level productivity data are not publicly available. Note that our focus on the manufacturing sector is similar to many empirical studies in corporate finance, such as those related to financing decisions. In addition, measuring productivity in the service industry is challenging, due to the difficulty in measuring outputs and labour inputs (see Mark (1982)).

1963, which is also the first year of the Fama-French factors. All productivity series are normalized to one in 1963. Following Fama and French, the productivity mimicking portfolio is constructed from July 1 in year t to June 30 in year t+1, and matched to productivity in 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. We use monthly returns in all of our analyses.

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]

To provide 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 suggests that stock returns vary positively with productivity growth. This relationship seems particularly strong in the post-1982 period, when the real effects of productivity changes are not swamped by high inflation rates during the two oil crises.[7]

[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 portfolio includes stocks from NYSE, AMEX, and NASDAQ. The trend in CRSP is the exact opposite of the trend in the S&P500: Manufacturing's relative significance declined in the overall U.S. market, but increased

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[7] The correlation between these two series is 0.24 for the whole sample period, but 0.54 after 1982.

within blue chip stocks. This difference is no doubt attributed to the rapid growth of the NASDAQ market in the 80's and the 90's. 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 have decreased dramatically to 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 the other sectors. Within the S&P500, however, manufacturing grew to represent more than half of the index in both firm count and market capitalization.

Table 2 reports the average annual productivity level, the stock price index, firm size, book-to-market ratio, as well as the correlation among these variables. The total sample includes 10,741 4-digit SIC industry-year observations. The stock price index is normalized to one in 1963, as is the productivity level. The stock price index in a given year is one plus the cumulative return since 1963.

One hypothesis is that higher profits due to increased productivity are competed away in more competitive industries, thereby reducing any impact on stock market returns. We use the Herfindahl index to measure the degree of competition, where the index is calculated as the sum of squared shares of each firm within an industry, measured using market capitalization. Hou and Robinson (2006) and Massa, Rehman, and Vermaelen (2007) measure industry concentration using the Herfindahl index.[8] The intuition is that the higher the Herfindahl index, the more concentrated the industry is.

8 The Herfindahl index is superior to the concentration ratio because concentration ratios ignore the number of firms within the industry. 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 this difference into account, whereas the concentration ratio does not.

Hence, there is an 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 boom. Prior to that, the technological advance was pioneered by mostly established firms with significant market power and high Herfindahl index values.

[Table 2]

Panel B of Table 2 reports the average correlation amongst the variables in Panel A. 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).

Next, 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 calculate the difference between the mean industry return in the top productivity quintile and that in the bottom quintile for each month from July in year t to June of year t+1. 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. 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 firm, SMB_M. The latter generates 1.94 percent annually in average excess returns, while HML_M generates 4.22 percent. Although the SMB and the HML for manufacturing firms have smaller excess returns compared to those from the full CRSP sample, they are still highly 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.[9]

[9] 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 that this has a significant impact on our results. First, 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 in average returns, not firm-specific information. In fact, ignoring the comings and goings of firms may actually underestimate the productivity premium: Highly productivity industries attract newcomers 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

Consistent with our argument, most of the productivity factors are positively correlated with SMB, and all of them are negatively correlated with HML. Hence, in general terms, we can say that productivity does affect returns in the capital market and that as hypothesized, it is closely related to the Fama-French size and book-to-market factors.

[Table 3]

III. Can Productivity Help Explain Stock Returns?

III.A Factor Loading on Productivity Portfolios

To see whether productivity helps explain stock returns, we employ the following four factor time-series model:

$$R_t = \alpha + \beta_m \times e\_R_{mt} + \beta_{SMB} \times e\_SMB_t + \beta_{HML} \times e\_HML_t + \beta_{PF} \times PFSIC4Q_t + \varepsilon_t \quad (3)$$

where R_t is the monthly excess return on the test portfolio, R_{mt} is the monthly CRSP value-weighted excess return, $PFSIC4Q_t$ is the monthly productivity factor, and e_R_{mt}, e_SMB_t, and e_HML_t are the monthly residuals from the following regressions:

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

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

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

where, and ε_t and e_t are i.i.d. error terms. The e_t's capture the variations in market excess return, SMB, and HML that are unrelated to the variations in productivity.

The above specification is designed, first of all, to test the hypothesis that productivity affects stock returns as Figure 1 suggests. In particular, we expect the productivity factor to have a bigger impact on small firms and on growth (i.e., low book-to-market, or B/M) firms. Second, it is designed to examine whether market excess return, SMB, and HML still have an impact on stock returns after controlling for productivity.

The dependent variable, R_t, is the return on three different test portfolio groups. 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. These three portfolio groups are identical to those used by Fama and French (1993).

Panel A of Table 4 shows the results for the first set of portfolios sorted by size. The productivity beta, β_{PF}, is highly significant, and its magnitude decreases monotonically with size. Hence, in accordance with our hypothesis, productivity has a bigger impact on smaller firms than on larger ones. The residual impact of the market excess return, as measured by β_m, is also highly significant, but it is fairly uniform across different size portfolios. The residual impact of SMB and HML is mostly significant as well, except for two larger cap portfolios. Note that the sign of the e_SMB_t beta actually turns negative in the 9th and 10th decile 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. In addition, the productivity betas are larger in magnitude than the betas of e_SMB_t and e_HML_t.

[Table 4]

Panel B of Table 4 shows the results for test portfolios formed on B/M deciles. Again, the productivity beta, β_{PF}, is positive. However, the relationship between B/M and β_{PF} is non-linear and U-shaped: Both high and low B/M portfolios have larger 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 shows 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 portfolios 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 are consistent with Schumpeter's argument that productivity changes generate new industries (captured here by small, growth firms), and the destructive forces of capitalism make them risky.

Note that the residual of HML isn't able to explain high growth firms (first quintile by B/M within each size quintile); it either has the wrong sign, or is statistically insignificant. Also, the residual of SMB has the wrong sign for high value firms (fifth quintile by size). However, overall, one cannot dismiss the observation that the residuals of SMB and HML have important explanatory power in the rest of the regressions, suggesting that in addition to proxying for productivity, size and B/M are robust risk factors in their own right.

III.B Asset Pricing Tests

The results in the previous section provided informal evidence that productivity helps explain the cross-section of stock returns. We now turn to two formal asset pricing tests: the classic two-pass Cross-Sectional Regression (CSR) model[10] and the Stochastic Discount Factor (SDF) model.

III.B.1 Two-pass CSR approach

In the two-pass CSR model, we first run a time-series regression for *each* test portfolio. Using the estimated portfolio betas, we then run a cross-sectional regression, and estimate the risk premium for each factor. This procedure is summarized as follows.

$$R_{it} = \alpha_i + \beta_i' \times f_t + \varepsilon_{it} \qquad (4)$$

$t = 1, 2, \dots. T$ for each test portfolio i; and

$$\overline{R_{it}} = \hat{\beta}_i' \times \lambda + \varepsilon_i \qquad (5)$$

$i = 1 \dots n$.

[10] This approach is the most widely used asset pricing test. See for example, Fama and French (1992), Harvey and Siddique (2000), Lettau and Luvdigson (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).

where R_{it} is the excess return on portfolio *i* in month *t*, $\overline{R}_{it}$ 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 test portfolios, and *T* is the number of monthly observations in the sample.[11]

We estimate (5) using Generalized Least Squares (GLS), to account for the fact that the residuals may be correlated with each other. To assess whether the linear specification is correct, we report Shanken (1985)'s Cross-Sectional Regression Test (CSRT) statistic. This statistic measures the aggregate expected return errors; its finite sample distribution under the null hypothesis is provided by Shanken.

III.B.2. Stochastic Discount Factor Approach

The other asset pricing test we perform follows the Stochastic Discount Factor (SDF) approach. It can be 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 (1), which in excess return format is:

[11] This method is equivalent to Fama and MacBeth (1973) if the errors are uncorrelated over time, which may not be an unreasonable assumption if returns are fairly independent.

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

where γ is the SDF, and R_i is the excess return on 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 problematic for the following two reasons. First, the specification test statistic is not invariant to an affine transformation of the factors. Second, the SDFs of competing models can have very different means, thus complicating the task of model comparison. Kan and Robotti recommend an alternative specification that defines the SDF as a linear function of the de-meaned factors:

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

With de-meaned factors, the vector of risk premiums is equal to:

$$\lambda = var(f)b$$

As Cochrane (2001) explains, when factors are correlated, we should test H_0: b_j=0, to see whether or not to include factor *j* in an asset pricing model, rather than test H_0: λ_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 H_0: b_j=0, then we should include factor f_j when we price assets.

The literature compares the performance of competing asset pricing models using the Hansen and Jagannathan (1997) distance (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 represents the maximum pricing error of a portfolio of excess returns that has a unit second moment. The smaller is the HJ distance, the smaller is the pricing error. Kan and Robotti (2008) suggest that a modification of the HJ distance 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 HJ distance to compare model performance in this paper. We also employ Shanken (1992)'s correction to the standard errors of λ , to account for the fact that the betas estimated in the first step are used as regressors in the second step, thus creating an errors-in-variables problem.[12]

III.B.3 The Empirical Models

Our goal is to address the following two questions in the asset pricing tests: i) does productivity help price assets in the presence of other factors? And ii) do the popular factors, SMB, HML, and momentum, proxy 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):

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

[12] 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 his correction is made.

Model 4 (Fama and French with PFSIC4Q and momentum factor, UMD):

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

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 by the productivity factor. Model 4 is further augmented by the Fama and French version of the momentum factor, *UMD*.

The dependent variable, R_t, is the excess return on the test portfolio. To generate dispersion across the factors, we perform a three-way independent sort. All equities in our manufacturing sample are sorted into three portfolios according to productivity, size, and B/M. Hence, we have 27 equally-weighted portfolios formed from the intersection of the three independent sorts. Each portfolio has 474 monthly observations. Table 5 displays the formation and the mean excess return of each portfolio.

[Table 5]

III.B.4. Empirical Results

Consider first the results from the two-pass CSR model. The first step of the model involves 27 time-series regressions, i.e., one for each of the test portfolio. Figure 2 summarizes the estimated betas of (or loadings on) the productivity factor, *PFSIC4Q*, for the four factor model with orthoganalized residuals in Table 4. The portfolios are ordered according to Table 5. The productivity betas are positive and significant for all of the test portfolios. Further, they monotonically decrease with size, in the same way as for the model in Table 4, but the relationship with B/M is not as clear. However, within each of the size-B/M portfolio, the beta is the highest in the highest productivity portfolio.

[Figure 2]

Panels A and B of Table 6 shows the results from the SDF approach, with Panel A for the vector of pricing coefficients, *b*, and Panel B for the vector of risk premiums, λ. First, the pricing coefficients of *PFSIC4Q* factor are positive and significant at five percent in Models 3 and 4. This result suggests that *PFSIC4Q* helps price assets, even in the presence of SMB, HML, and UMD. Second, Panel A shows that HML is highly significant in all four models, while *SMB* is never significant, and neither is UMD. Hence, our results suggest that size and momentum are not useful in pricing assets in the manufacturing sector. Finally, the probability value of the modified HJ distance is close to zero, thus rejecting the hypothesis that the aggregate pricing error is zero at one percent. So it appears that there are other factors that may be important in explaining the cross-sectional variations in stock returns that are not considered here. Across the four models, the modified HJ distance in Model 4 is the smallest. This means that any misspecification present in Model 4 translates into a smaller pricing error than in the other three models.

[Table 6]

Panels C of Table 6 shows the risk premium estimates from the two-pass CSR model. Rounded off to four digits, the estimated λ.'s are the same as those from the SDF model in Panel B. This confirms Cochrane (2001) and Jagannathan and Wang (2002) that the apparently "new" SDF approach is almost identical to the traditional CSR method. The risk premium results in Panels B and C can be summarized as follows. First, the productivity risk premium is positive, although it is only significant at 10 percent in Models 3 and 4, as is the case for the market risk premium, M. (Note that the estimated market risk premium is quite reasonable: In Model 4, it is 0.50 percent per month, which translates to about six percent per annum.) Second, HML is a robust risk factor that is priced across all four models. However, the size (SMB) and momentum (UMD) premiums are not priced. Finally, Shanken (1995)'s CSRT statistics are significantly different from zero at one percent for all four models, again suggesting model mis-specification.[13]

One might be troubled by the drop in statistical significance in the risk premium estimation. Ang, Liu, and Schwarz (2008) suggest that the issue may lie in the use of portfolios - as opposed to individual stocks - in asset pricing tests. They show that while portfolios improve the estimation of betas, they lead to higher asymptotic standard errors in the risk premium estimates.

The poor performance of the momentum factor for manufacturing stocks contrasts with the results from existing studies that use the whole CRSP database. To investigate, we construct a momentum factor using stocks from the manufacturing sector only. Following Fama and French, we build six value-weighted portfolios based on size and returns in (-12, -2) months to create the manufacturing UMD. The latter has a mean of 0.5 percent per month, in contrast to a mean of 0.9 percent for the full CRSP sample. Hence, the momentum premium in the manufacturing sector is considerably lower, and the difference is *not* due to size, as the way UMD is constructed, it has already neutralized the size effect. In order to explore the impact of past returns only, we follow Jegadeesh and Titman (1993) and create an alternative momentum factor based solely on

[13] We also tested the four models on 25 equally-weighted size/BM portfolios for the whole NYSE/AMEX/NASDAQ database obtained from Ken French's website. The test results are similar to those in Table 6.

past returns. We first sort stocks into deciles based on returns in (-12, -2) months, and construct a portfolio that longs stocks in the highest return decile and shorts stocks in the lowest return decile, with a one-month holding period. We find that this momentum factor has a mean of -0.4 percent. We conclude that momentum in manufacturing is much weaker than that in the full CRSP sample.

We have shown that productivity is a statistically significant risk factor. An important question to ask is whether it is economically significant. Consider the impact of ignoring productivity on returns. As shown in Model 4, Panel C of Table 6, the productivity premium is 0.0030 per month. If we multiply it by one cross-sectional standard deviation (i.e., the standard deviation of the productivity beta estimates in the first step of the two-pass CSR approach), it translates into an excess return of 0.91 percent on an annual basis. This is economically significant because the Fama-French factors and momentum are already controlled for.

IV. Productivity and Market Structure

Next, we examine the impact of market structure on the relationship between productivity and stock returns. The Herfindahl Index measures the degree of concentration in each industry. It is constructed as the sum of squared market shares across all firms in the industry. Generally speaking, the larger the Herfindahl index, the less competitive the industry is, and vice versa. There are two opposite arguments about the relationship 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 matter of survival. 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 a concentrated industry (ie a high Herfindahl index), larger firms have the capability, in terms of 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; we calculate the equally weighted monthly returns for each 2-digit SIC industries. Since Table 2 reveals that the correlation between productivity and the Herfindahl index changes sign around 1990, we divide the sample into two sub-periods, and run a pooled OLS regression on the panel data.

Table 7 shows the test results. The loading on the productivity factor itself is always positive and significant in the two sub-samples. However, the sign of the coefficient estimate of the interaction term for productivity and the Herfindahl index changes from insignificantly positive to significantly negative in the second sub-period. 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, firms in more competitive industries 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 as to the impact of industry competition and productivity on equity returns.

[Table 7]

V. Conclusion

In this paper, we examine the effect that productivity may have on stock returns. We create a productivity factor using 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.

Consistent with our hypothesis, productivity has a robust, positive impact on stock returns. We also expect productivity to come from small, growth firms. Indeed, we find that the productivity factor is positively 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 size portfolios, the productivity beta decreases monotonically with size. In other words, 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 then examine through asset pricing tests whether productivity is priced, and we find that it is indeed, even after controlling for SMB, HML, and the momentum factor, UMD. 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 stock 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.

References

Ang, R., J. liu, and K. Schwarz. Using stocks or portfolios in tests of factor models. *Working Paper*, March 2008.

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.

Breeden, D, 1979. An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics* 7, 265–296.

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.

Constantinides, G. M., and D. Duffie, 1996, Asset pricing with heterogeneous consumers. *Journal of Political Economy* 104, 219–240.

Dittmar, R. F., 2002. Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. *Journal of Finance* 57, 369-403.

Fama, E. F., 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.

Fama, E.F., and J. MacBeth, 1973, Risk, return and equilibrium: Empirical tests. *Journal of Political Economy* 81, 607–636.

Ferson, W. E. and C. R. Harvey, 1993, The Risk and Predictability of International Equity Returns. *Review of Financial Studies* 6: 527-566.

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., 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.

Jegadeesh N. and S. Titman 1993, Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance 48, 65-91

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 C. Zhang, 1999. Two-pass Tests of Asset Pricing Models with Useless Factors. *Journal of Finance* 54, 204-235.

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.

Li, Q., M. Vassalou, and Y. Xing, 2006, Sector Investment Growth Rates and the Cross Section of Equity Returns. *Journal of Business* 79, 1637-1665.

Lintner, J., 1965. Security prices, risk and the maximal gains from diversification. *Journal of Finance* 20, 587-616.

Mark, J.A., 1982. Measuring productivity in service industries. *Monthly Labor Review online* 105.

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.

Piazzesi, M. & S., Martin & T., Selale, 2007. Housing, consumption and asset pricing. *Journal of Financial Economics* 83, 531-569.

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.

Shanken, J, 1992. On the estimation of beta-pricing models. *Review of Financial Studies,* Oxford University Press for Society for Financial Studies 5, 1-33.

Sharpe, W. 1964. Capital asset prices: a theory of market equilibrium under conditions of uncertainty. *Journal of Finance* 19, 452-442.

Schumpeter, J., 1942. Capitalism, socialism and democracy. Harper.

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

Young, Alwyn, 1995. The Tyranny of numbers: Confronting the statistical realities of the East Asian growth experience, *Quarterly Journal of Economics* 110-3, 641-680.

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.

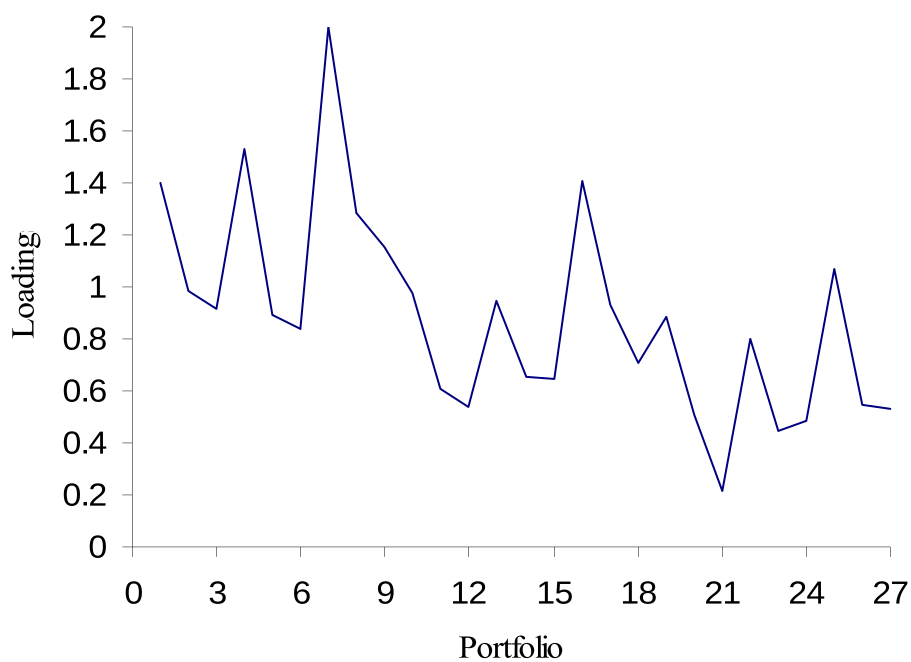

Table 1
Summary Statistics on the Manufacturing Sector, 1963-2002

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

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

Panel B: Relative Importance of the Manufacturing Sector: Snapshots

	Manufacturing as a Percentage of:			
	Number of Firms		Market Capitalization	
Year	CRSP	S&P500	CRSP	S&P500
1963	50	32	56	31
1983	26	40	42	35
2002	16	54	34	51

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

	Average Across All Manufacturing Industries				Correlation between Productivity Level and the Herfindahl index
Year	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(%) Mean	Median	Correlation with SMB	Correlation with HML
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
Time-Series Regressions

We report below the results from the following three models, in which we regress the market excess return, SMB_t and HML_t on the productivity factor, respectively. There 474 monthly observations. The residuals from the models, e_R_{mt}, e_SMB_t and e_HML_t, are used in the regressions below.

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

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

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

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							
		PFSIC4Q	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							
		PFSIC4Q	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

			Beta Coefficient Estimates							
			Four-Factor Orthogonal Model							
Size from Small to Big	B/M from Low to High	Mean Excess Return	*PFSIC4Q*	t-stat	e_R_{mt}	t-stat	*e_SMB*	t-stat	*e_HML*	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 5
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 6
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-pass cross-sectional GLS regression approach. Monthly data for M, SMB, HML, and UMD are obtained from Ken French's website. $PFSIC4Q_t$ is the monthly productivity factor. 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
Productivity					9.1439**	2.06	10.2398**	2.21
M	2.3540**	2.10	4.7889***	3.32	4.2254***	2.80	4.5648***	2.93
SMB			1.0854	0.62	-0.3603	-0.18	-0.4806	-0.25
HML			9.7195***	4.12	11.9289***	4.61	12.6528***	4.77
UMD							2.2331	0.82
mHJ distance	0.4195		0.3641		0.3506		0.3483	
p-value	<0.001		<0.001		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					0.0027	1.63	0.0030*	1.76
M	0.0048**	2.10	0.0046*	1.89	0.0046*	1.82	0.0050*	1.88
SMB			0.0005	0.28	0.0001	0.06	0.0002	0.11
HML			0.0057***	3.03	0.0063***	3.15	0.0062***	3.17
UMD							0.0005	0.13

Panel C: Risk premium estimates from the two-pass CSR approach
(Estimated using Generalized Least Squares)

	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	0.0030*	1.86	1.79
M	0.0048**	2.22	2.22	0.0046**	2.15	2.15	0.0046**	2.14	2.13	0.0050**	2.26	2.25
SMB				0.0005	0.32	0.32	0.0001	0.07	0.07	0.0002	0.13	0.13
HML				0.0057***	3.37	3.32	0.0063***	3.66	3.58	0.0062***	3.59	3.50
UMD										0.0005	0.14	0.13
CSRT	0.1740			0.1230			0.1098			0.1071		
p-value	0.0000			0.0003			0.0012			0.0011		

Table 7

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	
	Coefficient estimate	t-stat	Coefficient estimate	t-stat
Constant	0.007***	17.67	0.006***	9.18
e_M	0.974***	101.63	0.974***	101.61
e_SMB	0.968***	66.85	0.969***	66.82
e_HML	0.291***	18.62	0.292***	18.64
PFSIC4Q	1.067***	49.55	1.031***	27.62
Herfindahl			0.005	1.22
PFSIC4Q*Herfindahl			0.257	1.17
F	6226		4151	
adj R^2	0.80		0.80	

Panel B: January 1990 - December 2002

	Model 1		Model 2	
	Coefficient estimate	t-stat	Coefficient estimate	t-stat
Constant	0.006***	8.10	0.003**	2.80
e_M	1.017***	47.38	1.021***	47.83
e_SMB	0.580***	25.60	0.577***	25.63
e_HML	0.693***	22.95	0.688***	22.89
PFSIC4Q	0.775***	26.07	0.955***	21.41
Herfindahl			0.018***	3.24
PFSIC4Q*Herfindahl			-0.990***	-5.38
F	763		524	
adj R^2	0.49		0.50	