Labor Leverage,

Firms' Heterogeneous Sensitivities to the Business Cycle,

and the Cross-Section of Expected Returns

François Gourio*

October 2007

Abstract

Corporate profits are volatile and highly procyclical in the aggregate, but there is substantial heterogeneity across firms in the extent of this procyclicality: I document that firms with lower productivity or higher book-to-market have more procyclical profits. A simple static profit maximization problem can rationalize this. Firms which have more procyclical profits should also have higher betas and expected returns. Estimating an asset pricing model with aggregate productivity and aggregate real wage as factors validates this prediction. This economic story helps account for the size and value premia, and yields rich empirical implications by linking firms' real and financial characteristics.

Keywords: Cross-Section of Returns, Book-to-Market, Value Premium, Productivity Heterogeneity, Operating Leverage.

JEL codes: E44, G12.

---

*Boston University, Department of Economics, 270 Bay State Road, Boston MA 02215. Email: fgourio@bu.edu. This paper is a major revision of Chapter 3 of my University of Chicago dissertation, and is related to the cross-sectional results of my job market paper, "Operating Leverage, Stock Market Cyclicality, and the Cross Section of Returns". I am grateful to many seminar audiences and many people for their comments, and especially to my dissertation committee: Lars Hansen, Fernando Alvarez, John Cochrane, and Anil Kashyap, as well as Frederico Belo, Vito Gala, Simon Gilchrist and Adrien Verdelhan. All errors are mine.

1 Introduction

What determines a firm's riskiness? This is a crucial question both for asset pricing and for corporate finance. Financial economists usually measure the risk of a firm as the covariance of its stock return with some aggregate risk factor, but rarely explain the source of this covariance. Since risk is driven by aggregate shocks, we need to understand why some firms are more sensitive to aggregate shocks, i.e. to the business cycle. But there is little work analyzing which real characteristics of firms drive this sensitivity. Where does a stock's beta come from? The interest in this question is compounded by the findings of Fama and French (1992, 1996) that firms with a high book-to-market ratio have high expected returns. Is book-to-market an indicator of firms riskiness, if so why?

I propose and test a simple technology-based model of firms' earnings. This theory explains why some firms are more exposed to the business cycle. My model relies on two sensible assumptions: first, the aggregate real wage is smoother than aggregate productivity over the business cycle; second, firms differ in their capital shares (or operating margins). The key mechanism is as follows: because the wage is smooth, revenues are more cyclical than costs, making the residual - profits (or earnings) - highly procyclical. Firms with low productivity are more procyclical since the gap between revenues and costs is smaller, so that they benefit disproportionately from an increase in productivity which is not matched by a similar-sized increase in costs. I call this mechanism a "labor leverage". The mechanism is formally similar to financial leverage, but it is conceptually different since it does not depend on debt. My mechanism is closer to the "operating leverage": in fact, this paper can be seen as a microfoundation for the "operating leverage", since I am specific about the reason why costs are less cyclical than revenues. An important difference between my theory and the existing literature is that I show that the key ingredient is not that costs are fixed, but rather that aggregate productivity is more procyclical than the aggregate wage. Importantly, my model yields new empirical implications.

The key empirical results of the paper lie in section 3, which shows that these empirical implications are supported by the data. First, there is a large heterogeneity in earnings cyclicality across firms. In particular, firms with high book-to-market and firms with low productivity have more procyclical earnings. Moreover, their earnings are more exposed to changes in aggregate total factor productivity (TFP) and the aggregate real wage, as predicted by my model.

I then turn to the implications of my model for expected returns. (These implications require additional assumptions, because I need to specify a discount factor and extend the static model of earnings to a dynamic environment. In contrast, the labor leverage mechanism holds under mild assumptions.) The theory states that firms with low productivity or low capital shares have high earnings betas on aggregate productivity growth, and low betas on aggregate real wage growth. I evaluate a simple asset pricing factor model, where the two risk factors are productivity growth and wage growth: the difference in earnings betas should then lead to differences in average (or expected) returns. I find that this simple factor model fits the expected returns of the 25 Fama-French portfolios well, though it cannot match the return on the small-growth portfolio

Overall, the "labor leverage" mechanism leads to rich new empirical implications by linking (*i*) a firm's characteristics (productivity and capital shares), (*ii*) its real behavior (the elasticity of sales, employment and earnings to an aggregate shock) and (*iii*) its financial characteristics (the firm's betas and its average return).

The two key assumptions - wage smoothness and heterogeneity in capital shares or productivity - are well-established stylized facts. The standard deviation of the wage is half that of GDP, and the wage is not strongly correlated with aggregate productivity (see Abraham and Haltiwanger (1995), or Table 1). Productivity heterogeneity has been emphasized in the recent industrial organization and trade literature (see e.g. Bartelsman and Doms (2000) for a survey). In the typical four-digit industry, the ratio of the labor productivity of the 25th centile producer to the 75th centile producer is about 2. The ratio of the labor productivity of the 90th centile producer to the 10th centile producer is about 4. If one uses TFP instead of labor productivity, the productivity differentials are somewhat smaller, but still large, respectively 1.4 and 2.[1] Controlling for observables such as vintage or capital intensity reduces only partly the observed productivity heterogeneity. Like the recent trade and I.O. literature, my model takes productivity as exogenous, and explores the implications for earnings cyclicality and stock returns.

To my knowledge, the Schumpeterian idea that low productivity firms are more procyclical has not been tested with modern data, though Bresnahan and Raff (1991) give interesting evidence on auto factories during the Great Depression.[2]

Outline of the Paper

The remaining part of the introduction relates the paper to the existing literature. Section 2 studies the static model of earnings. Section 3 presents empirical evidence on the heterogeneity across firms in exposure of earnings to the business cycle; this is a test of the model of section 2. Section 4 derives the implications of the earnings model for betas and expected returns under some additional assumptions, and section 5 estimates a factor model on the 25 Fama-French portfolios to test the results of section 4. Section 6 concludes.

Related Literature

This paper is mostly related to two strands of the literature. First, a large empirical literature in finance uses parsimonious factor models to fit the cross-section of expected returns. In this literature, the challenge is to find macroeconomic variables which proxy for the marginal utility of wealth, and which also covary with returns of some stocks (e.g., value stocks or small stocks). Recently several macroeconomic variables have been proved successful, such as durables or housing consumption, and the interaction of consumption growth with labor income or the consumption-wealth ratio.[3] However there has been much less work attempting to answer the natural question: what is the economic link between these variables and value stocks? For instance, in a highly influential paper, Lettau and Ludvigson (2001) show that when the consumption-wealth ratio is

[1] These numbers are drawn from Syverson (2004), Table 1.

[2] See Caballero and Hammour (1994) and De Long (1990) for a discussion of the Schumpeterian view and a different model.

[3] A very partial list includes Lettau and Ludvigson (2001), Lustig and Van Nieuwerburgh (2005), Pakos (2006), Piazzesi, Schneider and Tuzel (2007), Santos and Veronesi (2006), and Yogo (2006).

high relative to its trend, the covariance between value stocks and consumption growth is high. What is the characteristic of value firms that explains this behavior? This covariance is measured empirically, but there is no economic interpretation of why it is high when the consumption-wealth ratio is high. Hence, the question is interesting from a theoretical point of view. From a practical point of view, since some of these factor models are often rather atheoretical and there is a risk of "fishing" for the successful factor model or "overfitting" the Fama-French portfolios, understanding the source of the estimated betas is an important question. From an econometric point of view, my model delivers a cross equation restriction: the stock's beta is not a free parameter.

This paper is also related to the recent literature on production-based models of the cross-section of returns. Following the seminal work of Berk, Green and Naik (1999) and Gomes, Kogan and Zhang (2003), several papers address the question of the sources of firm riskiness (key contributions include Carlson, Fisher and Giammarino (2005, 2006), Cooper (2006), Gala (2005), Panageas and Yu (2006) and Zhang (2005)). Most of these papers emphasize that firms differ in the mix of growth options and assets in place, and these two components may have a different riskiness. Hence, these papers concentrate on the important differences investment behavior across firms. In contrast, my paper abstracts from investment for simplicity, and the differences between growth and value are entirely driven by differences in earnings cyclicality. As I show, these differences appear to be empirically relevant. Clearly, these lines of research are complementary.

2 A Model of Firms' Earnings

In this section, I introduce a static model of firms' earnings, and I use it to derive, for each firm, the elasticities of its earnings, sales and employment to a macroeconomic shock, as a function of the firm's idiosyncratic productivity. I discuss the conditions under which these elasticities are different across firms. In appendix A, I discuss some additional implications of this model for sales and employment cyclicality of this, and I present some additional robustness analysis.

2.1 Elasticities of Earnings

Consider a firm which operates a constant return to scale production function in capital k and labor n : $y = zxF(k,n)$. The firm's idiosyncratic productivity is x while z denotes aggregate productivity.[4] As is standard in the short-run analysis of profit maximization, I assume that capital is fixed within the period and labor is fully adjustable: the firm decides each period how many people to hire, given the aggregate real wage w. Total earnings (or variable profits, or operating income) is:

$$\pi(x,k,z,w) = \max_{n \geq 0} \{zxF(k,n) - wn\}. \tag{1}$$

Note that x and k are firm-level variables while z and w are aggregate variables. Given current idiosyncratic and aggregate productivity x and z, the firm chooses n by equating the marginal product of labor and the market wage:

$$zxF_2(k,n) = w.$$

Total revenues, or sales, are $y(x,k,z,w) = zxF(k, n(x,k,z,w))$, and the capital share is:

$$s_K = \frac{\pi(x,k,z,w)}{y(x,k,z,w)}.$$

This is the share of revenue that is not paid to labor. I will refer from now on to this number as the capital share, but it is also known as the operating margin (the ratio of operating income to sales) in the empirical finance literature, and it is a measure of profitability. Simple algebra shows that this capital share is a function only of the ratio xz/w : $s_K = s_K(xz/w)$. Next, applying the envelope theorem to $\pi(x,k,z,w) = \max_{n \geq 0} \{zxF(k,n) - wn\}$, yields the response of earnings to

[4] For simplicity I refer to x and z as productivity. However, they might also reflect demand shocks, and hence could be labelled shocks to profitability.

a change in aggregate productivity or in the wage:

$$\frac{\partial \log \pi(x,k,z,w)}{\partial \log z} = \frac{1}{s_K}, \qquad \frac{\partial \log \pi(x,k,z,w)}{\partial \log w} = -\frac{s_L}{s_K},$$

where $s_L = 1 - s_K$. Of course in general equilibrium changes in aggregate productivity will be correlated with changes in the aggregate wage. To discuss the total cyclicality of earnings, I combine these formulas and obtain the total effect of a shock to aggregate productivity on current earnings, for a given wage response to a productivity shock $\frac{\partial \log w}{\partial \log z}$:

$$\begin{aligned} \frac{d \log \pi(x,k,z,w)}{d \log z} &= \frac{\partial \log \pi}{\partial \log z} + \frac{\partial \log \pi}{\partial \log w}\frac{\partial \log w}{\partial \log z}, \\ &= \frac{1}{s_K(xz/w)}\left(1 - s_L(xz/w)\frac{\partial \log w}{\partial \log z}\right). \end{aligned}$$

This formula is the key element of this paper. It implies directly the following result.

Result 1

- If the wage responds one-for-one to an aggregate productivity shock, i.e. $\partial \log w / \partial \log z = 1$, then $d \log \pi / d \log z = 1$ is independent of x, i.e. all firms' earnings rise by one percent if aggregate productivity z rises by one percent.

- If on the other hand, the wage is smoother than productivity, i.e. $\partial \log w / \partial \log z < 1$, then $d \log \pi / d \log z > 1$, i.e. earnings are more procyclical than productivity, and moreover earnings are more procyclical (i.e. $d \log \pi / d \log z$ is larger) in firms which have a lower capital share $s_K(zx/w)$.

In aggregate data, corporate profits (or earnings) are highly procyclical, and more volatile than total factor productivity (TFP) or GDP. It is well understood that an important reason for this fact is that labor compensation is relatively smooth and weakly correlated with TFP or GDP growth.[5] Table 1 gives some statistics that summarize these stylized facts: the volatility of the growth rate of before-tax profits is 3.63 times the volatility of the growth rate of GDP, and the

[5] For instance, Longstaff and Piazzesi (2004) note that " (...) the reason for the extreme volatility and procyclicality of corporate earnings is that stockholders are residual claimants to corporate cash flows. Thus, the compensation of workers is a senior claim to cash flows." See also Gomme and Greenwood (1995).

slope coefficient in a regression of profit growth on TFP growth is 3.56. On the other hand, the volatility of real wage growth is 0.49 that of GDP growth, and the slope coefficient of wage growth on TFP growth is 0.34.

Result 1 is the cross-sectional counterpart of this fact: firms which have high labor costs "leverage" the smoothness of wages. As labor costs do not respond as much as revenues to changes in macroeconomic conditions, profits (revenues minus labor costs) are procyclical, and the higher the share of labor, the more volatile the profits. The mechanism is algebraically analogous to financial leverage or operating leverage, but it is conceptually different: it does not rely on fixed costs (i.e., costs which cannot be adjusted) or fixed debt payments. Rather, it depends solely of the relative cyclicality of the wage and productivity[6]: if wage and productivity were equally cyclical, there would not be any heterogeneity. Importantly, this mechanism has strong empirical implications, which I test in Section 3 using Compustat data.

Note that we can rewrite this result in a way more amendable to empirical work. Taking a first-order approximation of the profit function and using result 1, the change in earnings between two dates $t-1$ and t is approximately:

$$\Delta \log \pi_t(x,k,z,w) = \Delta \log k_t + \frac{1}{s_K(x)}\Delta \log z_t + \left(1 - \frac{1}{s_K(x)}\right)\Delta \log w_t + \frac{1}{s_K(x)}\Delta \log x_t, \tag{2}$$

where $s_K(x)$ is the capital share at time $t-1$, $\Delta \log z_t$ (resp. $\Delta \log w_t$) is the change in *aggregate* productivity (resp. the aggregate wage) between $t-1$ and t, and $\Delta \log k$ and $\Delta \log x$ are the *firm-specific* changes in the stock of capital and idiosyncratic productivity. This is the equation that I will use in my empirical work.

[6] I do not model the reason for the smoothness of wages. This wage smoothness could be due to firms insuring workers partially against aggregate shocks; or it could be due solely to technology, if the marginal product of labor is less volatile than the average product of labor.

2.2 Sources of Heterogeneity

The heterogeneity in sensitivities to aggregate shocks that I demonstrated arises only if firms have different capital shares. This heterogeneity in capital shares could be due to firms operating different technologies, e.g. firms which have Cobb-Douglas production functions with different parameters. Alternatively, differences in capital shares may be due to differences in productivity. Given the wide interest in productivity heterogeneity in the economics literature (especially trade and industrial organization), it is interesting to see the conditions under which this arises. The question is, what are the production functions F such that firms with the same technology but different productivities x have different shares $s_K(xz/w)$. Clearly, a simple Cobb-Douglas production function does not satisfy this property: in this case, each firm equates its marginal product of labor to the common wage; moreover since the marginal product of labor is proportional to the average product of labor with a Cobb-Douglas production function, there is no cross-sectional heterogeneity either in labor productivity (output per employee) or capital shares (operating margins). This is in stark contrast with the data, where there is a large heterogeneity in measured labor productivity and in capital shares, as I explained in the introduction. Hence it seems that an empirically successful production function should generate these two correlations. This leads me to examine what conditions on the production function F are necessary to obtain these correlations.

Result 2

Assume a constant return to scale production function with idiosyncratic productivity x and capital k, i.e. $y = zxF(k, n)$. Then a firm with a higher TFP x has a higher output per worker and a higher capital share if and only if the elasticity of substitution is less than unity.

Proof: see Appendix B.

Hence the low elasticity of substitution case is the only one, within constant returns, that can generate a positive correlation between TFP, labor productivity, and capital shares. The intuition for this result is that when the elasticity of substitution is low, the technology does not allow much flexibility in changing output, and as a result good productivity shocks translate into a higher output per worker rather than a higher number of workers. (Some examples are presented in Appendix C). Moreover, this assumption of a low elasticity of substitution is empirically appealing: many pieces of equipment operate in the short-run under nearly fixed proportions - think of a truck which requires exactly one driver, or a machine on an assembly line which needs to be monitored by one worker.

As in the trade or industrial organization literature, I do not model the source of the underlying heterogeneity in productivity, which is poorly understood. Most likely, the very large heterogeneity is due both to mismeasurement of inputs, differences in organization and management, and to random shocks to demand or supply conditions.

3 Testing the Earnings Model: Cross-Sectional Differences in Earnings Cyclicality

This section tests empirically for the mechanism proposed in section 2 by estimating the equation (2). This amounts to measuring the differences in earnings cyclicality across firms. The regressions document two main empirical facts. First, firms with lower productivity or lower operating margins have more procyclical earnings. Second, value firms with a high book-to-market ratio have lower margins and productivity, and are more procyclical than growth firms. Moreover, this larger procyclicality is precisely a larger sensitivity on TFP and a lower (i.e. more negative) sensitivity to the aggregate real wage. These patterns are in accord with the model's predictions. This higher cyclicality implies in theory a higher cash flow beta and hence can potentially explain why value stocks are more risky. The predictions for cash flow betas will be developed and tested in sections 4 and 5.

The first subsection considers panel data evidence, while the second subsection considers portfolio-level evidence. It is more natural to test the model with panel data regressions, but using portfolios makes my results more directly comparable to those of the empirical finance literature, and it also allows me to include observations with negative earnings (about 12% of all firm-year observations), since portfolios usually have positive earnings even when many individual firms do not.

3.1 Panel Data Evidence

3.1.1 Specification

My key results come from two simple regressions. The first specification is the one implied by equation (2). I treat the change in idiosyncratic productivity as an error term. Result 3 states that $\frac{1}{s_K(x)}$ is a function of productivity. For simplicity I assume the function is linear, so that I can replace the inverse capital share by a measure of productivity. The equation that I estimate is thus:

$$\Delta \log OI_{i,t} = \alpha + (\beta_1 + \delta_1 x_{i,t-1}) \Delta \log TFP_t + (\beta_2 + \delta_2 x_{i,t-1}) \Delta \log w_t + \gamma_1 x_{i,t-1} + \gamma_2 \Delta \log K_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where i indexes firms and t time. This equation simply measures the effect of idiosyncratic productivity, denoted by $x_{i,t-1}$ on the sensitivity of earnings $OI_{i,t}$ to the business cycle. Earnings are measured as operating income, and I discuss below the various measures of productivity that I use. I estimate this equation using a simple pooled OLS regression. The prediction of the model is that $\delta_1 < 0$ and $\delta_2 > 0$: firms with low idiosyncratic productivity react more positively to an increase in aggregate productivity, and more negatively to an increase in the aggregate real wage, as per result 1. One possible concern is that productivity differences are to some extent driven by across-industry variation. As a robustness check, I also run this regression with a full set of industry dummies and industry dummies interacted with GDP growth.

I also use a second regression:

$$\Delta \log OI_{i,t} = \alpha + (\beta + \delta x_{i,t-1}) \Delta \log GDP_t + \gamma_1 x_{i,t-1} + \gamma_2 \Delta \log K_{i,t} + \varepsilon_{i,t}. \tag{4}$$

This specification uses GDP growth to measure the business cycle; it is a simple and robust measure that is likely to be better measured than TFP or the real wage. The key prediction of the model is that the coefficient δ on the cross-term $x_{i,t-1}\Delta \log GDP_t$ is negative: firms with low idiosyncratic productivity have more procyclical earnings. For this specification, I perform the same robustness check, by adding industry dummies and industry dummies interacted with TFP growth and with real wage growth. More robustness tests are discussed below.

3.1.2 Data

I use annual data from Compustat; this is an unbalanced sample with 43,125 firm-year observations from 1963 to 2004. I use only firms with a December fiscal-year, so as to line up the timing of the firm-level data with macroeconomic aggregates. As is standard in the literature, I exclude firms from the financial sector and utilities. Because my specification requires operating income to be positive, I restrict the sample to all firm-year observations for which operating income (item 13) is positive.[7] The data construction is detailed further in Appendix E.

3.1.3 Measuring Productivity

Measuring productivity in Compustat is difficult because there is no data on value-added. Hence, I use three alternative measures of productivity. The first measure is the market-to-book ratio, defined as in Fama and French (1992). (I flip the sign from book-to-market to market-to-book so that the three measures of productivity are all higher for more productive firms.) This market-to-book ratio is often used as a proxy for productivity in the industrial organization literature (e.g. Lindenberg and Ross, 1981). Indeed, Dwyer (2001) shows by merging Compustat and plant-level Census data that market-to-book is strongly correlated with TFP and labor productivity. My second measure is the ratio of operating income to sales, i.e. the operating margin (item 13 over

[7] The section 3.2 performs the same tests using portfolio-level data, which include the firms with negative earnings. One other possibility to incorporate the firms with negative earnings is to use $\log(OI + \xi)$ instead of $\log(OI)$, where ξ is a positive number. All of my results are robust to this extension. I conclude that dropping observations with negative earnings does not alter the results significantly.

item 12). This is a natural measure of capital share in the absence of data on materials.[8] Finally, I estimated a simple profitability measure with the following procedure. In each year, and for each industry, I run a cross-sectional regression of the log of operating income (item 13) on log capital (item 8):

$$\log(OI_{i,t}) = \alpha_{t,k} + \beta_{t,k} \log K_{i,t} + \varepsilon_{i,t},$$

estimated for each t and each industry k, across firms i. The residual $\varepsilon_{i,t}$ is my profitability measure.[9] This procedure is essentially an estimation of the operating profit function.

To make the results easier to interpret, I normalize the productivity variables $x_{i,t}$ to have mean zero and unit standard deviation in each year (i.e. $x_{i,t}$ is defined as the residual in a regression of log productivity on a full set of time dummies, and this residual is rescaled to have variance one in each year). This does not affect the substance of the results, but it makes the interpretation of the coefficients δ_1, δ_2 in (3) more transparent: δ_1 simply measures the change in sensitivity of earnings to TFP growth if log-productivity is one cross sectional standard deviation above the average.

Table 2 presents the correlations between the three productivity variables $x_{i,t}$. Given the normalization, each variable has mean zero and standard deviation one in each year. This table shows that the three measures of productivity are significantly correlated.

3.1.4 Main Results

Table 4 reports the main results, obtained from estimating (3), for each of the three productivity variables, with or without the industry controls. For conciseness this table and the ones that follow report only the key coefficients δ_1 and δ_2 and the associated standard errors. In reading Table 4, it is useful to know that the average sensitivity of profits to TFP growth is 4.87, and

[8] I also used return on assets (ROA, operating income over assets (item 13 over item 6)), which yields very similar results.

[9] In related work, Yang (2006) also estimates a Solow residual. I believe the difference between his results and mine is that he estimates his equation in first-difference, so that his residual identifies firms which have had a high increase in productivity, whereas I identify firms with a high *level* of productivity.

the average sensitivity of profits to wage growth is -1.88 (this is documented in Table 3). Table 4 reveals that a high market-to-book ratio is associated with less cyclical profits. The results are statistically significant and economically large: looking at the first row, a firm which has a log market-to-book ratio one standard deviation above the average has a sensitivity of profits to GDP growth equal to 3.16 ($= 4.87 - 1.71$), while a firm which has a log market-to-book ratio one standard deviation below the average has a sensitivity of 6.58 ($= 4.87 + 1.71$). Hence, the latter firm is much more exposed to business cycle fluctuations. These effects are smaller once industry controls are included, but they remain significant. This result holds for all three definition of productivities. Turning to the coefficient δ_2 (the coefficient on the interaction term between firm-level productivity and aggregate wage growth), we see that it is significantly positive for two productivity measures (market-to-book and the profitability measure) as predicted by the model. However, the estimates using the last productivity measure (operating margin) are insignificant.

Table 5 produces the result when productivity is measured as the average over time of the productivity measure, for each firm, rather than as the current period productivity. This is an attractive specification from an empirical point of view if measurement error in productivity is large and transient, since averaging over time will improve the precision in this case. Consistent with this intuition, the results of Table 5 are starker than in Table 4.

Table 6 reports the simplest results, using the specification (4) with GDP growth. I report only the results when productivity is measured as an average over time as in Table 5, (but they are very similar if I use the current value of productivity). The interaction term δ is always negative and highly significant: firms with high market-to-book, high margins or high profitability are less cyclical.

A potential alternative explanation for these results is the "fixed cost" effect usually associated with the textbook operating leverage story: firms have costs which do not depend on the level of production, so a given increase in sales increase their profits by a large amount, and low productivity firms have higher operating leverage since their sales barely cover their fixed costs.[10] I test this possibility by running regressions of the form:

$$\Delta \log OI_{i,t} = \alpha + \beta \Delta \log S_{i,t} + \gamma x_{i,t-1} + \delta x_{i,t-1} \Delta \log S_{i,t} + \varepsilon_{i,t}.$$

where S = real sales. This regression checks if an increase in sales translates into a more-than-proportional increase in earnings, and if this amplification is greater for less productive firms. The results, displayed in Table 7, indicate that the interaction term δ is small and sometimes insignificant. A one standard deviation decrease in productivity increases the elasticity of profits to sales by 0.12 at best, i.e. it increases from about 1.30 to 1.42. Hence, it seems that the "operating leverage" story based on fixed costs does not account for the differences in cyclicality that I am interested in.[11] A particular focus of interest is on the differences between growth and value, which the operating leverage mechanism does not explain at all (Table 7 rows 1 and 2), and for which my model gives a plausible mechanism backed by significant estimates (Tables 4 and 5, rows 1 and 2).

3.1.5 Robustness

As we saw in Tables 4 through 6, the results are still highly significant (though the magnitude is smaller) when I control for industry effects; also the results are generally robust across the three measures of productivity. I performed several other robustness checks.[12] The results are robust to variations in the Compustat sample, for instance if I restrict the sample to manufacturing firms, or to the subsample 1978-2004 rather than 1963-2004. Hence, compositional effects due to changes in the Compustat universe are not driving the results. These results are also very robust to the inclusion of firm fixed effects, or time effects, or to the exclusion of $\Delta \log K_{it}$ from the regressions.

Tables 8 and 9 check if the results are affected by the measure of profits that I use. In this

[10] Mathematically, earnings equal sales less fixed costs, $E = S - FC$, so that $\frac{\Delta E}{E} = \frac{S}{S-FC}\frac{\Delta S}{S}$.

[11] Gulen, Xing and Zhang (2004) find similar results.

[12] The results are available upon request.

tables, I use net income (item 172 in Compustat), which is profit after tax, after interest and after depreciation. Of course this measure of profit is more volatile than the one I used above (i.e. item 13): the average sensitivity of profits to TFP growth is 7.24 rather than 4.87 (see row 4 of Table 3). Table 8 presents the results when productivity is measured as the average over time, while Table 9 uses the current value of productivity. All of my results hold with this different measure of profits: firms with lower margins or higher book-to market have a higher sensitivity to TFP growth and a more negative sensitivity to wage growth: in table 8, a one standard deviation decrease in market-to-book increases the sensitivity to TFP by 3.04 point, and reduces the sensitivity to wages by 2.17 point. This implies that a firm which is one standard deviation above the mean in book-to-market has a sensitivity to TFP (resp. wage) of 10.28 (resp. -5.61), while a firm which is one standard deviation below the mean in book-to-market has a sensitivity to TFP (resp. wage) of 4.20 (resp. -1.27). The magnitude of these differences is an interesting empirical fact which is new (to the best of my knowledge).

The model also predicts that firms with low productivity have higher responses of sales and employment to an increase in productivity. I tested for this using the same methodology and also found that firms with lower productivity have more cyclical sales employment, but the differences are smaller than for profits.[13]

3.2 Portfolio-level Evidence

I now turn to portfolio-level evidence. I use 10 portfolios sorted by book-to-market created by Fama and French (1996).[14] To conduct my analysis, I first replicate the portfolio construction of Fama and French using CRSP/Compustat. I compute for each portfolio the sum of the operating income of all the firms in portfolio i at time t, and I construct the sum of the operating income

[13] These results are available upon request.

[14] I also used their set of 25 portfolios, with very similar results. However some of these portfolios have negative operating income for a few years, especially the small value portfolio. This makes it impossible to apply my regressions, because my model assumes that earnings are always weakly positive.

at year $t+1$ of all the firms that were in portfolio i at time t.[15] This allows me to compute the growth rate of operating income (i.e., earnings) for each portfolio. Table 10 documents that high book-to-market portfolios have lower operating margins and a lower return on asset, consistent with Fama and French (1995).

As in the previous section, I next test if the portfolios with higher book-to-market have more cyclical profits. For each portfolio i of stocks, I run the time-series regression:

$$\Delta \log OI_{i,t} = \alpha_i + \beta_i \Delta \log GDP_t + \varepsilon_{i,t}, \tag{5}$$

and I also run the regression with TFP growth and wage growth:

$$\Delta \log OI_{i,t} = \alpha_i + \beta_i \Delta \log TFP_t + \gamma_i \Delta \log w_t + \varepsilon_{i,t}, \tag{6}$$

Table 11 (first panel) shows the regression coefficient estimates of (5). The estimates of β_i are clearly increasing in book-to-market. The spread in regression coefficients between high and low book-to-market is economically and statistically important: an increase of 1% of GDP increases earnings of the low book-to-market firms by 1.42% according to the point estimate, while it increases the earnings of high book-to-market firms by 5.52%.

Table 12 (first panel) reports the results from estimating (6); the coefficient estimates β_i and γ_i are displayed in Figure 1. The high book-to-market portfolios are highly sensitive to TFP growth, with $\beta_1 = 1.41$ for the first (growth) portfolio and $\beta_{10} = 7.78$ for the tenth (value) portfolio; moreover, the high book-to-market portfolios are, as predicted, more sensitive in absolute value to changes in the wage: the coefficient on wage growth is $\gamma_1 = -0.21$ for the growth portfolio and $\gamma_{10} = -4.42$ for the value portfolio. The economic magnitude of these spreads in coefficients

[15] Since firms change portfolios over time, I need to keep track of where the firms were in year t to compute the growth between t and $t+1$ of the operating income of firms in portfolio i at t. I drop firms which disappear between t and $t+1$. This could bias my results if firms with a high book-to-market are more likely to drop out *and* the firms that drop out are less cyclical. The latter condition seems rather unlikely. I also used a balanced subsample and found similar results. Also, the results I find are consistent with the panel data evidence which relies on an unbalanced sample. I conclude that selection bias is unlikely to be driving my results.

is important, since these coefficients imply that profits of value firms are much more exposed to shocks to productivity or wages, which are variables that certainly affect investors.

Table 11 also provide estimates for a similar regression with net income[16], sales, and employment. The results for net income are similar, and stronger, than the results for earnings. The sensitivities of sales and employment are also generally increasing, especially for the extreme portfolios, but the effects are smaller, consistent with the panel data evidence.

4 Dynamic Implications for Betas and Expected Returns

In this section, I consider the implications of my earnings model for expected return and betas. This section requires making additional assumptions to go from static earnings to present values: first we need to show how the static model of the previous section is extended to a dynamic environment (first subsection), and second we need to take a stand on which shocks are priced by the stochastic discount factor (second subsection). The end product that I obtain is the firm's beta on each of the two factors, as a function of its idiosyncratic productivity x, and the implied expected stock return. Because my model focuses on risk to firms' earnings, my results really apply to the "cash flow beta", as in Campbell and Vuolteenaho (2004) or Bansal, Dittmar, and Lundblad (2006).

4.1 Dynamic Cash Flow Model

The model of earnings studied in section 2 is static. To transform it into a dynamic cash flow model, we need to explain how capital and productivity evolve over time. I make two strong simplifying assumptions which allow me to obtain clear results in this section.[17]

First, firms have a constant idiosyncratic productivity x. This is an approximation to the more realistic case of a stochastic, but highly persistent productivity x. Changes in productivity

[16] Net income is negative in some periods for various portfolios. I restrict the sample of the net income regression to 1963-1991 and do not run it for portfolio 10. For these portfolios and this sample, I have positive net income at all times and for all portfolios.

[17] Note that these assumptions are not necessary for the results of sections 2 and 3.

over time do not seem very important for my analysis; an increase in productivity will lead to an idiosyncratic change in cash flows, which, being idiosyncratic, bears no risk premium. An increase in x would also lead to a change in the systematic risk of the firm, but as long as productivity is highly persistent (as it seems to be empirically, see Bartelsman and Doms (2000)), this systematic risk will change slowly (unless risk is highly sensitive to productivity).

The second simplification is that capital is fixed. In reality, firms do adjust capital in response to a good productivity shock to scale up their operations. There are however several cases where my approximation may be good. First, if adjustment costs are large, firms will adjust capital slowly towards its desired value. Second, when investment is irreversible, it may be impossible to adjust capital downward. Finally, in some cases, when investment is tied to a specific market, it may be inefficient to scale up or down: think of Wal-Mart opening a new store in some location; this investment is largely sunk; as long as the profitability of that location is not extremely low or high, it is probably inefficient to adjust its size. However, this assumption would not fit all firms. Clearly investment matters, as emphasized in the recent literature (Berk, Green and Naik (1999) and the other papers cited in introduction). The point of this paper is to emphasize that there is a large heterogeneity in cyclicality of earnings, on top of the heterogeneity in investment behavior.

4.2 Betas and Returns

In this section, I take as exogenous the aggregate productivity process $\{z_t\}$ and the wage process $\{w_t\}$, and I specify a process for the discount factor $\{m_t\}$. I then deduce the implied betas and expected returns of the different firms given the earnings model.

Equation 2 implies, given the additional assumptions of constant capital and productivity made in this section:

$$\Delta \log \pi_t(x) = \frac{1}{s_K(x)} \Delta \log z_t + \left(1 - \frac{1}{s_K(x)}\right) \Delta \log w_t.$$

To derive the implications for returns and firms' betas, I now introduce an exogenous log-normal discount factor. I assume that:

$$\log M_{t,t+1} = -\lambda_z \Delta \log z_{t+1} - \lambda_w \Delta \log w_{t+1}.$$

First note that since I am interested only in risk premia, the conditional mean is irrelevant. Second, this discount factor could be justified, for instance, if there is a representative consumer with constant relative risk aversion γ, and his consumption equals $c_t = \left(z_t^{\lambda_z} w_t^{\lambda_w}\right)^{1/\gamma}$. But the overall motivation is more general: in any general equilibrium model, the innovations to the stochastic discount factor must depend on the aggregate shocks; hence this formulation is likely to be a good approximation to many models where productivity affects the aggregate economy, and there are additional shocks which are captured by the wage. Productivity shock clearly matter, at least for the long run. Moreover, a large empirical literature in macroeconomics suggests that there are independent shocks which affect labor supply (and thus the aggregate wage) without directly affecting productivity (Chari, Kehoe and Mcgrattan (2006), Christiano and Eichenbaum (1992), Hall (1997), Mulligan (2002)). This justifies my specification.

I also assume the following linear model for productivity and wages:

$$\begin{pmatrix} \Delta \log z_{t+1} \\ \Delta \log w_{t+1} \end{pmatrix} = \begin{pmatrix} A_{zz}(L) & 0 \\ A_{wz}(L) & A_{ww}(L) \end{pmatrix} \begin{pmatrix} \varepsilon_{t+1}^z \\ \varepsilon_{t+1}^w \end{pmatrix},$$

with $\{\varepsilon_t^z\}$ and $\{\varepsilon_s^w\}$ orthogonal. The top-right 0 restriction reflects a definition: ε_{t+1}^z is the fundamental innovation to productivity, and ε_{t+1}^w is the innovation to the part of wages that is not generated by productivity.

Given the assumed discount factor and the processes for productivity and wage, standard computations (see appendix D) yield the risk premium on a firm with productivity x :

$$\log\left(\frac{E_t R_{t+1}(x)}{R_{t+1}^f}\right) = \left(\lambda_z + \lambda_w A_{wz}(0)\right)\sigma_z^2 \left(\frac{1}{s_K(x)} A_{zz}(\rho) + \left(1 - \frac{1}{s_K(x)}\right) A_{wz}(\rho)\right) + \lambda_w \sigma_w^2 \left(1 - \frac{1}{s_K(x)}\right) A_{ww}(\rho).$$

There are two risk factors, productivity growth and wage growth, and the betas of asset x on each factor are endogenously determined by the model as a function of productivity x:

$$\begin{aligned}\beta_z(x) &= \frac{Cov_t(r_{t+1}(x), \Delta \log z_{t+1})}{Var_t(\Delta \log z_{t+1})} = \left(\frac{1}{s_K(x)} A_{zz}(\rho) + \left(1 - \frac{1}{s_K(x)}\right) A_{wz}(\rho)\right), \\ \beta_w(x) &= \frac{Cov_t(r_{t+1}(x), \Delta \log w_{t+1})}{Var_t(\Delta \log w_{t+1})} = \left(1 - \frac{1}{s_K(x)}\right) A_{ww}(\rho).\end{aligned}$$

It is helpful to consider some special cases.

Case 1: if the wage is constant over time, then $A_{wz}(\rho) = A_{ww}(\rho) = 0$, and TFP growth is the only risk factor. In this case, the risk premium is $\lambda_z \sigma_z^2 A_{zz}(\rho)/s_K(x)$, which is the product of the market price of risk $\lambda_z \sigma_z^2$ times the sensitivity of the cash flows $\frac{1}{s_K(x)}$ of firm x, times the measure of the persistence of the shock $A_{zz}(\rho)$. The term $A_{zz}(\rho)$ captures the fact that an increase of z is persistent and thus affects profits persistently. The firm's beta on the aggregate risk factor $\Delta \log z_{t+1}$ is in this case:

$$\beta_z(x) = \frac{Cov_t(r_{t+1}(x), \Delta \log z_{t+1})}{Var_t(\Delta \log z_{t+1})} = \frac{1}{s_K(x)} A_{zz}(\rho),$$

which shows that the real profit sensitivity $\frac{1}{s_K(x)}$ *determines* directly the firm's beta $\beta_z(x)$, and given the results of section 2, firms with low productivity x have higher $\frac{1}{s_K(x)}$, higher betas and higher mean return.

Case 2: another simple case is when both productivity and wages are driven by the same shock process, so that their conditional correlation is unity; that is, $\varepsilon_{t+1}^w = 0$ and as a result, $A_{ww}(\rho) = 0$. The risk premium is now:

$$\log\left(\frac{E_t R_{t+1}(x)}{R_{t+1}^f}\right) = (\lambda_z + \lambda_w A_{wz}(0))\, \sigma_z^2 \left(\frac{1}{s_K(x)} A_{zz}(\rho) + \left(1 - \frac{1}{s_K(x)}\right) A_{wz}(\rho)\right),$$

and the firm's beta is

$$\beta_z(x) = \frac{1}{s_K(x)} A_z(\rho) + \left(1 - \frac{1}{s_K(x)}\right) A_w(\rho).$$

This formula shows that the covariance with aggregate productivity (the only asset pricing factor) is now driven not only by the response of profits to productivity shocks, but also by the response of profits to the wages induced by the productivity shocks. Since $1/s_K(x)$ is decreasing in x, the risk premium is decreasing in x if and only if $A_z(\rho) > A_w(\rho)$. Since $Var(\Delta \log z_t) = A_z(1)\sigma_z^2$ and $Var(\Delta \log w_t) = A_w(1)\sigma_z^2$, for $\rho \to 1$ (the empirically relevant case) this condition amounts to saying that the wage is less volatile than the productivity. Hence, this special case shows how the relative smoothness of wage and productivity is key for determining risk premia; when the wage is smoother than productivity, low productivity firms have higher expected returns. This is essentially a present-value extension of the labor leverage mechanism of section 2.

General case: as before, the beta on TFP growth is decreasing in productivity x if and only if the 'wage smoothness' condition $A_{zz}(\rho) > A_{wz}(\rho)$ is verified, i.e. the variance of wages *due to the productivity shock* is less than the variance of productivity *due to the productivity shock*. Moreover, the beta on wage growth is increasing in productivity given that $\frac{1}{s_K(x)}$ is decreasing in x. Finally, putting the two parts together, the condition for low productivity firms to have higher expected returns is now:

$$(\lambda_z + \lambda_w A_{wz}(0))\, \sigma_z^2\, (A_{zz}(\rho) - A_{wz}(\rho)) - \lambda_w \sigma_w^2 A_{ww}(\rho) > 0.$$

Given $\lambda_z > 0$ and $A_{zz}(\rho) > A_{wz}(\rho)$, this will be true when the market price of TFP risk $\lambda_z \sigma_z^2$ is higher than the market price of the wage risk $\lambda_w \sigma_w^2$. Note that $\lambda_w > 0$ corresponds to a 'labor hedging motive': shocks to the wage are priced, and investors require a risk premium to hold securities which pay off when the wage is high; but $\lambda_w < 0$ is also possible, if investors' marginal utility of wealth is positively correlated with wage shocks. I now turn to the empirical evaluation of these implications.

5 Testing the Implications for Betas and Returns

The model of section 4 states that a firm's risk is determined by how much its cash flows are exposed to shocks in aggregate productivity and in the aggregate real wage. I test this idea by estimating an asset pricing factor model where the two factors are aggregate productivity growth and aggregate real wage growth. I evaluate this factor model by gauging its ability to price the twenty-five portfolios sorted by size and book-to-market created by Fama and French (1996), which have attracted much attention in the literature. Table 13 gives the mean excess returns for each of the 25 portfolios, revealing the well-known patterns of the value and size premium.

To estimate this factor model, I follow Cochrane (2001) and Yogo (2006) and apply the generalized method of moments (GMM) to the linearized version of the model. Given that I fit the model only on excess returns, I can normalize the mean of the stochastic discount factor to 1. I thus specify

$$M_{t+1} = 1 - b_z \Delta \log z_{t+1} - b_w \Delta \log w_{t+1},$$

where $\Delta \log z_{t+1}$ is (demeaned) productivity growth and $\Delta \log w_{t+1}$ is (demeaned) real wage growth. To follow the setup of section 4, which assumed that the wage shocks had no effect on productivity, I use as my wage growth series the residual of wage growth on productivity growth. This transformation does not affect at all the statistics of fit, since the space spanned by the two factors is the same, but it makes the interpretation of the results easier by considering 'pure' wage changes as opposed to wage shocks induced by productivity, which have different effects.[18]

The set of moments is $E\left(M_{t+1} R^e_{i,t+1}\right) = 0$ for $i = 1, ..., 25$. These moments can be equivalently presented in the 'expected return-beta' form, i.e.

$$E\left(R^e_{i,t+1}\right) = b_z Cov\left(R^e_{i,t+1}, \Delta \log z_{t+1}\right) + b_w Cov\left(R^e_{i,t+1}, \Delta \log w_{t+1}\right),$$

[18] The overall effect of this transformation is not large in any case, because the wage is not highly correlated with productivity.

which expresses the theory that the risk premium on asset i is determined by the discount factor loading on each of the two factors (b_z and b_w), and the extent to which the asset covaries with each of the two factors.

Before turning to the estimation, it is useful to consider some stylized facts that drive the results. It is useful to compute and examine the betas implied by simple OLS regressions. Hence, tables 14 and 15 present the beta of the excess return on the two factors, obtained from a time-series regression for each of the 25 portfolios:

$$R_{t+1}^{e,i} = \alpha_i + \beta_{z,i} \Delta \log z_{t+1} + \beta_{w,i} \Delta \log w_{t+1} + \varepsilon_{i,t+1}.$$

These betas are depicted in Figures 2 and 3 respectively. Two facts stand out: first, value stocks and small stocks have higher betas on TFP growth, with the notable exceptions of the small and small-medium growth portfolios. Second, value stocks and small stocks have a lower beta on wage growth. The differential in wage betas is especially high for the small growth - small value spread, and for value generally, while the effect on size is more mixed. A simple way to summarize this is to say that the correlation of the return on the HML asset (long value and short growth) with the change in real wage is -0.18 (standard error 0.09).

These stylized facts translate into the estimation of the factor model, which results are displayed in Table 16. I present both the first-stage estimates, which use the identity matrix to weight the moment conditions, and the second-stage estimates, which use the optimal weighting matrix of Hansen (1982).[19] The data is quarterly from 1952-I to 2002-IV. The factor loadings b_{TFP} and b_w on the stochastic discount factor are positive for TFP and negative for the wage; the loading on TFP is highly significant both in the first-stage and in the second stage, while only the second-stage estimate is significant for the loading on the wage. Since the factors are orthogonal by construction, the results for the loadings b are similar to the results for the 'market price of risks',

[19] I use 5 lags to compute the Newey-West covariance (aka spectral density) matrix. This choice is based on the lag selection proposed by Andrews (1991).

defined by $\lambda = Cov(f)^{-1}b$ where f is the vector of factors, b is the vector (b_{TFP}, b_w) and λ is the vector $(\lambda_{TFP}, \lambda_w)$. The negative sign of b_w and λ_w is surprising: agents require risk premia to hold securities which pay off when the wage goes *down*. This is the opposite of a natural labor income hedging demand. This negative coefficient suggests that the shocks which drive wages down are actually good for stockholders, perhaps because these are shocks to the distribution of income between capital owners and 'workers'.[20]

This 'asset demand' by investors interacts with the betas of the portfolios: as explained above, growth stocks and small stocks have higher beta on TFP and a lower beta on the wage. Hence, both factors lead to a higher premium for small or value stocks than for big or growth stocks and this helps improve the fit of the model. Of course, the finding of a negative price of risk for the wage is important: it is not enough that small and value stocks are more affected by TFP and (in absolute value) by the wage than other stocks, it must also be that investors care about these covariances.

For comparison purposes, the estimation results from the CAPM and the CCAPM are displayed in Table 17 and the estimation results from the three-factor Fama-French model are displayed in Table 18. Figure 4 presents the standard cross-sectional plots of fitted returns vs. mean excess returns for four different models: the CAPM, the CCAPM, the Fama-French three factor model, and my two-factor productivity-wage model. Clearly, the CAPM fits very poorly, the CCAPM fits much better, except for the small-growth portfolio, and my model is a marked improvement over the CCAPM. This is reflected in the mean absolute pricing error (MAE) which is 0.369% for my model, 0.555% for the CCAPM, and 0.288% for the three-factor Fama-French model (all these numbers are per quarter, for the first stage estimates; second-stage estimates yield a similar comparison). However, this plot also shows that the pricing error remains large in my model for two portfolios (the small-growth and the small-medium growth portfolios), despite the significant wage beta.

[20] This result is related to Lustig and Van Nieuwerburgh (2007) who use a different methodology but also find that shocks to human capital are negatively related to shocks to financial wealth.

To summarize, the key empirical results from this exercise are the following: (1) there is a fair amount of dispersion across portfolios in the betas on TFP growth and on real wage growth; (2) as predicted by the model, high book-to-market portfolios have a higher beta on TFP growth and a lower beta on wage growth; finally (3) the discount factor assigns a negative price of risk to wage growth. Overall the model performs significantly better than the consumption CAPM, but the fit is worse than that of the multifactors modes of Fama and French (1996), or Yogo (2006).

6 Concluding Remarks

The main contribution of this paper is to propose a full-fledged story of firms' riskiness, starting from the firm's productivity and capital share, continuing with the cyclicality of its earnings, and finishing with the stock's beta and average return. The key idea is that costs and revenues have a different cyclicality. This "labor leverage" mechanism is robust, because the assumptions it requires are minimal. I document a large heterogeneity across firms in earnings sensitivities. Firms with low productivity, especially firms with high book–to-market, have more procyclical earnings: an increase in TFP benefits more to low productivity firms, and an increase in the real wage hurts them more. As a result, these firms' stocks have higher loadings on productivity growth, and smaller loadings on wage growth. This justifies their higher average returns. I find supporting evidencee: productivity and operating margins, profit elasticities to GDP or TFP, betas on TFP and the real wage, and average returns are all significantly correlated.

More fundamentally, this paper suggests that more attention should be paid to the modelling of the profit function, which is rarely the focus of research. In particular, the input prices that firms face affect significantly their earnings and their risk. It seems plausible that secular changes in the production structure or in input markets would induce changes in the risk and return of financial assets.

References

[1] Abraham, Katharine, and John Haltiwanger. 1995. "Real Wages and the Business Cycle" Journal of Economic Literature, 33(3):1215-1264.

[2] Andrews, Donald. 1991. "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation," Econometrica, 59 (1):817–858.

[3] Arias Andres, Gary Hansen and Lee Ohanian. 2006. "Why have business cycle fluctuations become less volatile?", NBER Working paper #12079.

[4] Bartelsman, Eric, and Dunne. 2001. "Understanding Productivity: Lessons from Longitudinal Microdata" Journal of Economic Literature, 38(3):569:594.

[5] Berk, Jonathan, Richard Green and Vanant Naik, 1999. "Optimal Investment, Growth Options and Security Returns", Journal of Finance 54(5):1553-1607.

[6] Bresnahan, Timothy, and Daniel Raff. 1991. "Intra-Industry Heterogeneity and the Great Depression: The American Motor Vehicles Industry, 1929-1935". The Journal of Economic History, 51(2):317-331.

[7] Caballero, Ricardo, and Mohamed Hammour. 1994. "The Cleansing Effect of Recessions". American Economic Review, 84(5): 1350-1368.

[8] Caballero, Ricardo, and Eduardo Engel. 1999. "Explaining Investment Dynamics in U.S. Manufacturing: A Generalized (S,s) Approach ", Econometrica, 67(4):783-826.

[9] Campbell, John. 1991. "A Variance Decomposition for Stock Returns". Economic Journal, 101(1):157-179.

[10] Campbell, John and Robert Shiller. 1988. "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors". Review of Financial Studies, 1(3):195-228.

[11] Campbell, John and Tuomo Vuolteenaho. 2004. “Bad Beta, Good Beta”. American Economic Review, 94(5):1249:1275.

[12] Carlson, Murray, Adlai Fisher and Ron Giammarino. 2004. “Corporate Investment and Asset Price Dynamics: Implications for the Cross-Section of Returns ”. Journal of Finance, 5(6):2577-2603.

[13] Carlson, Murray, Adlai Fisher and Ron Giammarino. 2006. “Corporate Investment and Asset Price Dynamics: Implications for SEO Event Studies and Long-Run Performance”. Journal of Finance, 61(3):1009-1034.

[14] Chari, V.V., Patrick Kehoe and Ellen McGrattan. 2007. “Business Cycle Accounting”. Econometrica, forthcoming.

[15] Christiano, Lawrence and Martin Eichenbaum. 1992. “Current Real-Business-Cycle Theories and Aggregate Labor-Market Fluctuations”, American Economic Review, 82(3):430-450

[16] Cochrane, John. 2001. “Asset Pricing”. Princeton University Press.

[17] Cooper, Ian. 2006. “Asset Pricing Implications of Non-Convex Adjustment Costs of Investment”. Journal of Finance, 61(1):139-170.

[18] De Long, John Bradford. 1990. “Liquidation cycles: old-fashioned real business cycle theory and the Great Depression”. NBER Working paper 3546.

[19] Dwyer, Douglas. 2001. “Plant-level productivity and the Market Value of a Firm”. Census Bureau CES working paper.

[20] Fama, Eugene and Kenneth French. 1992. “The Cross-Section of Expected Stocks Returns”. Journal of Finance, 47(2):427-465.

[21] Fama, Eugene and Kenneth French. 1995. “Size and Book-to-Market Factors in Earnings and Returns”. Journal of Finance, 50(1):131-155.

[22] Fama, Eugene and Kenneth French. 1996. "Multifactor Explanations of Asset Pricing Anomalies". Journal of Finance, 51(1):55-84.

[23] Gala, Vito. 2006. "Investment and Return". Mimeo, London Business School.

[24] Gomme, Paul and Jeremy Greenwood. "On the cyclical allocation of risk". Journal of Economic Dynamics and Control, 19:1-2, 91-124.

[25] Gomes Joao, Leonid Kogan, and Lu Zhang. 2003. "Equilibrium Cross Section of Returns". Journal of Political Economy, 114(4): 693-732.

[26] Gulen, Xing and Zhang. 2004. "Value vs. Growth: Cyclcial variations in expected returns". Working paper.

[27] Hall, Robert. 1997. "Macroeconomic Fluctuations and the Allocation of Time", Journal of Labor Economics, 15(1):S223-S250.

[28] Hayashi, Fumio. 1982. "Tobin's Marginal q and Average q: A Neoclassical Interpretation". Econometrica, 50(1):213-224.

[29] Lettau Martin and Sydney Ludvigson. 2001. "Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia Are Time-Varying". Journal of Political Economy. 109(6):1238:1287.

[30] Lindenberg Eric B. and Stephen A. Ross. 1981. "Tobin's q Ratio and Industrial Organization". The Journal of Business, 54(1):1-32.

[31] Longstaff, Francis and Monika Piazzesi. "Corporate earnings and the equity premium". Journal of Financial Economics, 74(3):401-421.

[32] Lustig, Hanno and Stijn Van Nieuwerburgh. 2005. "Housing Collateral, Consumption Insurance and Risk Premia: an Empirical Perspective." Journal of Finance, 60(3):1167:1219.

[33] Lustig, Hanno and Stijn Van Nieuwerburgh. 2007. "The Returns on Human Wealth: Good News on Wall Street is Bad News on Main Street" Review of Financial Studies, forthcoming.

[34] Mulligan, Casey. 2002. "A Century of Labor-Leisure Distortions". NBER working paper 8774.

[35] Pakos, Michal. 2004. "Asset Pricing with Durable Goods and Non-Homothetic Preferences". Mimeo, Carnegie-Mellon University.

[36] Panageas, Stavros, and Jianfeng Yu. 2006. "Technological Growth, Asset Pricing, and Consumption Risk". Mimeo, Wharton School.

[37] Piazzesi, Monika, Martin Schneider and Selale Tuzel. 2007. "Housing, consumption, and asset pricing". Journal of Financial Economics, 83(1):531-569.

[38] Santos, Tanos and Pietro Veronesi. 2006. "Labor Income and Predictable Stock Returns". Review of Financial Studies, 19(1):1-44.

[39] Syverson, Chad. 2004. "Product Substitutability and Productivity Dispersion". Review of Economics and Statistics, 86(2):534:550.

[40] Yang, Halla. 2006. "Firm productivity and expected returns". Working paper, HBS.

[41] Yogo, Motohiro. 2006. "A Consumption-Based Explanation of Expected Stock Returns". Journal of Finance, 61(2):539:580.

[42] Zhang, Lu. 2005. "The Value Premium". Journal of Finance, 60(1):67-103.

7 Appendix A

This appendix discusses the implications for sales and employment cyclicality of the model of Section 2, and presents some additional robustness analysis.

7.1 Elasticities of Sales and Employment

We can also derive the elasticities of sales and employment to aggregate productivity z or the aggregate wage rate w.

Result 3

Let σ be the elasticity of substitution of F. Then the labor demand $n(x,k,z,w)$ and output supply $y(x,k,z,w)$ of a firm satisfy:

$$\begin{aligned} \frac{\partial \log n}{\partial \log z} &= \frac{\sigma}{s_K}, & \frac{\partial \log n}{\partial \log w} &= -\frac{\sigma}{s_K}, \\ \frac{\partial \log y}{\partial \log z} &= 1+\sigma\frac{s_L}{s_K}, & \frac{\partial \log y}{\partial \log w} &= -\sigma\frac{s_L}{s_K}. \end{aligned}$$

The proof (see below) consists simply in differentiating labor demand. These equations show, unsurprisingly, that an increase in productivity increases employment and output, and an increase in the wage has the opposite effect. Putting these elasticities together, I infer the total responses of employment:

$$\begin{aligned} \frac{d\log n}{d\log z} &= \frac{\partial \log n}{\partial \log z} + \frac{\partial \log n}{\partial \log w}\frac{\partial \log w}{\partial \log z} \\ &= \frac{\sigma}{s_K(xz/w)}\left[1-\frac{\partial \log w}{\partial \log z}\right], \end{aligned}$$

and the total response of sales:

$$\begin{aligned} \frac{d\log y}{d\log z} &= \frac{\partial \log y}{\partial \log z} + \frac{\partial \log y}{\partial \log w}\frac{\partial \log w}{\partial \log z} \\ &= 1+\sigma\frac{s_L(xz/w)}{s_K(xz/w)}\left[1-\frac{\partial \log w}{\partial \log z}\right]. \end{aligned}$$

If the wage rises one-for-one with productivity, i.e. $\partial \log w / \partial \log z = 1$, employment does not respond to a change in aggregate productivity: firms do not find it profitable to hire more workers since their cost as increased as much as their productivity. In this case, output increases only by the amount of the productivity increase. On the other hand, if the wage increases by less than productivity, i.e. i.e. $\partial \log w / \partial \log z < 1$, there is a rise in employment at all firms and a further rise in output, beyond the increase directly due to productivity. This effect is stronger when the elasticity of substitution is higher, since in this case firms' technologies are more flexible. Finally, the increase is strongest for low capital share firms since they are more flexible at the margin.

- **Proof of Result 3:** let $u = zx/w$. The labor demand is $n = kg(u)$, with g defined implicitely by: $u \times F_2(1, g(u)) = 1$. Differentiating yields

$$g'(u) = -\frac{F_2(1, g(u))}{u \times F_{22}(1, g(u))},$$

hence

$$\frac{ug'(u)}{g(u)} = -\frac{F_2(1, g(u))}{g(u) F_{22}(1, g(u))}.$$

By constant return to scale, $F(1, g(u)) = F_1(1, g(u)) + g(u)F_2(1, g(u))$, and thus differentiating:

$$F_{12}(1, g(u)) = -F_{22}(1, g(u))g(u).$$

Since $\sigma = (F_1 \times F_2)/(F \times F_{12})$, we have

$$\begin{aligned} \frac{ug'(u)}{g(u)} &= -\frac{F_2(1, g(u))}{g(u)F_{12}(1, g(u))} \\ &= \frac{F_2(1, g(u))F_1(1, g(u))}{F(1, g(u))F_{12}(1, g(u))} \frac{F(1, g(u))}{g(u)F_1(1, g(u))} \\ &= \frac{\sigma}{s_K}, \end{aligned}$$

where the last line follows from $s_K = \frac{k \times zxF_k(k,n)}{zxF(k,n)} = \frac{kF_k(k,n)}{F(k,n)} = \frac{F_k(1,\frac{n}{k})}{F(1,\frac{n}{k})} = \frac{F_1(1,g(u))}{F(1,g(u))}$. Hence

$\frac{\partial \log n}{\partial \log z} = \frac{\sigma}{s_K}$, and the other results follow similarly.

7.2 Robustness

Intermediate Inputs and Decreasing Return to Scale

It is straightforward to extend the model and incorporate intermediate inputs and decreasing returns. Decreasing returns can be modeled as a fixed input, which I label 'intangible capital' (K^I) as opposed to tangible capital (K^T) which is measured. The profit function is:

$$\pi(x, K^T, K^I, z, p, w) = \max_{L,M} \left\{ zxF(K^T, K^I, N, M) - wN - pM \right\},$$

where intermediate inputs are denoted by M (with price p). The envelope theorem yields:

$$\frac{\partial \log \pi}{\partial \log z} = \frac{1}{s_K^T + s_K^I} \left(1 - s_L \frac{\partial \log w}{\partial \log z} - s_M \frac{\partial \log p}{\partial \log z} \right).$$

There are three novelties: (1) the cyclicality of the price of material inputs now also affects the cyclicality of profits ; (2) the coefficient on $\frac{\partial \log w}{\partial \log z}$ is $-\frac{s_L}{s_K}$ which is less than $1 - \frac{1}{s_K}$; (3) the coefficient in front of the parenthesis is lower than the inverse of the measured capital share.

The empirical implications are preserved:

In terms of the empirical implications, this can explain why the coefficient in fron.

Adjustment Costs to Capital

My results are derived under the standard assumption that capital is fixed within the period (i.e., there is a one-period time-to-build). Hence, the presence of adjustment costs to capital has no impact on the results.

8 Appendix B

- **Proof of Result 1: in the text.**

- **Proof of Result 2:**

Since $s_K(u) = \frac{uF(1,g(u))-g(u)}{uF(1,g(u))}$, a simple differentiation yields:

$$\frac{d\log s_K}{d\log u} = \frac{-g'(u)uF(1,g(u)) + g(u)F(1,g(u)) + g(u)ug'(u)F_2(1,g(u))}{\left(uF(1,g(u)) - g(u)\right)F(1,g(u))},$$

which is positive if and only if

$$-g'(u)uF(1,g(u)) + g(u)F(1,g(u)) + g(u)ug'(u)F_2(1,g(u)) > 0$$

$$1 - \frac{g'(u)u}{g(u)} > -\frac{ug'(u)}{g(u)}\frac{g(u)F_2(1,g(u))}{F(1,g(u))},$$

and given that $\frac{g'(u)u}{g(u)} = \frac{\sigma}{s_K}$ and $\frac{uF_2(1,g(u))}{F(1,g(u))} = s_L$, this is equivalent to the condition:

$$\begin{aligned} 1 - \frac{\sigma}{s_K} &> -\frac{\sigma}{s_K}s_L, \\ s_K &> \sigma(1 - s_L), \\ 1 &> \sigma. \end{aligned}$$

which proves the claim that $\frac{d\log s_K}{d\log u} > 0$ iff $\sigma < 1$. Moreover, under the same condition, output per worker (labor productivity) is increasing in productivity (TFP) since applying the elasticities found above yields:

$$\begin{aligned} \frac{\partial \log\left(\frac{y}{n}\right)}{\partial \log x} &= \frac{\partial \log y}{\partial \log x} - \frac{\partial \log n}{\partial \log x} \\ &= 1 + \sigma\frac{s_L}{s_K} - \frac{\sigma}{s_K} \\ &= 1 + \sigma\left(\frac{s_L - 1}{s_K}\right) \\ &= 1 - \sigma, \end{aligned}$$

so that firms with high TFP x also have high output per worker if and only if $\sigma < 1$.

- **Proof of Result 3:**

Let $u = zx/w$. The labor demand is $n = kg(u)$, with g defined implicitely by: $u \times F_2(1, g(u)) = 1$. Differentiating yields

$$g'(u) = -\frac{F_2(1, g(u))}{u \times F_{22}(1, g(u))},$$

hence

$$\frac{ug'(u)}{g(u)} = -\frac{F_2(1, g(u))}{g(u)F_{22}(1, g(u))}.$$

By constant return to scale, $F(1, g(u)) = F_1(1, g(u)) + g(u)F_2(1, g(u))$, and thus differentiating:

$$F_{12}(1, g(u)) = -F_{22}(1, g(u))g(u).$$

Since $\sigma = (F_1 \times F_2)/(F \times F_{12})$, we have

$$\begin{aligned} \frac{ug'(u)}{g(u)} &= -\frac{F_2(1, g(u))}{g(u)F_{12}(1, g(u))} \\ &= \frac{F_2(1, g(u))F_1(1, g(u))}{F(1, g(u))F_{12}(1, g(u))} \frac{F(1, g(u))}{g(u)F_1(1, g(u))} \\ &= \frac{\sigma}{s_K}, \end{aligned}$$

where the last line follows from $s_K = \frac{k \times zxF_k(k,n)}{zxF(k,n)} = \frac{kF_k(k,n)}{F(k,n)} = \frac{F_k(1,\frac{n}{k})}{F(1,\frac{n}{k})} = \frac{F_1(1,g(u))}{F(1,g(u))}$. Hence $\frac{\partial \log n}{\partial \log z} = \frac{\sigma}{s_K}$, and the other results follow similarly.

9 Appendix C: Examples for Section 2

I now consider some simple examples to illustrate my three results. In particular, example 2 shows that an alternative reason why firms may have different capital shares is the presence of fixed costs of production or overhead labor (this is a deviation from constant return and thus my results do not directly apply to this case).

Example 1. Cobb-Douglas $F(k, n) = k^{1-\alpha} n^{\alpha}$.

The optimal labor demand is $n = k \times d \times (xz/w)^{\frac{1}{1-\alpha}}$ where d is a constant. The output supply is $y = e \times k \times (xz/w)^{\frac{1}{1-\alpha}}$ where e is a constant. As a result the output per worker is e/d, independent of productivity. The operating margin (capital share) is $s = 1 - \alpha$, which is also independent of x, z, or w. As explained above, while this simple Cobb-Douglas production function is often used, it cannot reproduce the observed heterogeneity in measured productivity or capital shares. The intuition is that firms which have high productivity x firms scale up by hiring more labor, till they have the same marginal cost, and same output per worker, as less productive firms.

Example 2. Cobb-Douglas with Overhead labor $F(n) = k^{1-\alpha} (n - \overline{n})^{\alpha}$.

In this formulation, there is an overhead labor of $\overline{n}$, leading to a fixed cost (labelled in wages rather than units of output); hence there are increasing returns to scale. The optimal labor demand is $n = \overline{n} + d \times k \times (xz/w)^{\frac{1}{1-\alpha}}$ where d is a constant. The output supply is $y = e \times k \times (xz/w)^{\frac{1}{1-\alpha}}$ where e is a constant. Output per capita is thus $e/\left(d + \overline{n}\,(xz/w)^{-\frac{1}{1-\alpha}}\right)$ which is increasing and concave in xz/w. The capital share s_K is $1 - \frac{w}{e}\left(d + \overline{n}\,(xz/w)^{-\frac{1}{1-\alpha}}\right)$ which is increasing in xz and decreasing in w. This formulation is thus also capable of capturing the two key correlations (high x firms have higher productivity and higher capital share).

Example 3. Leontief production function $F(k,n) = \min(n,k)$.

This production function has constant returns in labor up to a capacity constraint k, after which the marginal product of labor is zero: hence, the marginal cost curve has an inverted-L shape. One particular case of it is the putty-clay model of Gilchrist and Williams (2001), simplified in Gourio (2007). With this formulation, two cases arise: either $zx \geq w$, and it is optimal to hire up to full capacity, hence labor demand is $n = g(zx/w) = k$, or $zx < w$, and it is optimal to not hire anyone, hence $n = g(zx/w) = 0$. Therefore, the output is $y = zxk$ for $zx > w$, and 0 for $zx < w$. Finally, the profit share is $(zx - w)$ for $zx > w$, and 0 for $zx < w$. This setup can thus also generate the key correlations.

Example 4. CES Production Function with Fixed Capital $F(k,n)$.

As proved above, high TFP firms have higher labor productivity and higher capital shares if and only if $\sigma < 1$.

10 Appendix D: Computation of the Risk Premia

In order to compute the risk premia, I use the Campbell-Shiller (1989) decomposition, which given the SDF and the assumption of a constant x yields:

$$r_{t+1}(x) - E_t r_{t+1}(x) = (E_{t+1} - E_t) \sum_{j \geq 0} \rho^j \Delta d_{t+j+1}(x).$$

We need to compute the covariance of the return with the innovation to the discount factor. Denoting logs by lowercase letters yields:

$$\begin{aligned}
\log\left(\frac{E_t R_{t+1}(x)}{R^f_{t+1}}\right) &= E_t r_{t+1}(x) - E_t r^f_{t+1} + \frac{1}{2} Var_t r_{t+1}(x) \\
&= -Cov_t\left(\log m_{t,t+1}, r_{t+1}(x)\right) \\
&= -Cov_t\left(\log m_{t,t+1} - E_t \log m_{t,t+1}, r_{t+1}(x) - E_t r_{t+1}(x)\right) \\
&= Cov_t \left(\begin{array}{c} \lambda_z\left(\Delta \log z_{t+1} - E_t \Delta \log z_{t+1}\right) + \lambda_w (\Delta \log w_{t+1} - E_t \Delta \log w_{t+1}), \\ (E_{t+1} - E_t) \sum_{j \geq 0} \rho^j \left(\frac{1}{s_K(x)} \Delta \log z_{t+j+1} + \left(1 - \frac{1}{s_K(x)}\right) \Delta \log w_{t+j+1}\right) \end{array} \right),
\end{aligned}$$

where the last line uses the definition of the SDF, the Campbell-Shiller decomposition, and the fact that there are no changes in discount rates, since the aggregate market price of risk is constant and productivity is constant over time for a given firm.

Recall the prediction formula of Hansen and Sargent (1980): if $x_t = B(L)\varepsilon_t$, then

$$(E_t - E_{t-1}) \sum_{j \geq 0} \beta^j x_{t+j} = B(\beta)\varepsilon_t.$$

Note that I can restrict $A_{zz}(0) = A_{ww}(0) = 1$, but $A_{wz}(0) \neq 1$ in general. Hence:

$$\log\left(\frac{E_t R_{t+1}(x)}{R^f_{t+1}}\right) = Cov_t\left(\begin{array}{c} \left(\lambda_z + \lambda_w A_{wz}(0)\right)\varepsilon^z_{t+1} + \lambda_w \varepsilon^w_{t+1}, \\ \left(E_{t+1} - E_t\right)\sum_{j\geq 0}\rho^j\left(\frac{1}{s_K(x)}\Delta\log z_{t+j+1} + \left(1 - \frac{1}{s_K(x)}\right)\Delta\log w_{t+j+1}\right) \end{array}\right)$$

$$= Cov_t\left(\begin{array}{c} \left(\lambda_z + \lambda_w A_{wz}(0)\right)\varepsilon^z_{t+1} + \lambda_w \varepsilon^w_{t+1}, \\ \left(E_{t+1} - E_t\right)\sum_{j\geq 0}\rho^j\left(\left(\frac{1}{s_K(x)}A_{zz}(L) + \left(1 - \frac{1}{s_K(x)}\right)A_{wz}(L)\right)\varepsilon^z_{t+j+1} + \left(1 - \frac{1}{s_K(x)}\right)A_{ww}(L)\varepsilon^w_{t+j+1}\right) \end{array}\right)$$

$$= Cov_t\left(\begin{array}{c} \left(\lambda_z + \lambda_w A_{wz}(0)\right)\varepsilon^z_{t+1} + \lambda_w \varepsilon^w_{t+1}, \\ \left(\frac{1}{s_K(x)}A_{zz}(\rho) + \left(1 - \frac{1}{s_K(x)}\right)A_{wz}(\rho)\right)\varepsilon^z_{t+1} + \left(1 - \frac{1}{s_K(x)}\right)A_{ww}(\rho)\varepsilon^w_{t+1} \end{array}\right)$$

$$= \left(\lambda_z + \lambda_w A_{wz}(0)\right)\sigma_z^2\left(\frac{1}{s_K(x)}A_{zz}(\rho) + \left(1 - \frac{1}{s_K(x)}\right)A_{wz}(\rho)\right) + \lambda_w\sigma_w^2\left(1 - \frac{1}{s_K(x)}\right)A_{ww}(\rho),$$

where $\sigma_w^2 = Var(\varepsilon^w_{t+1})$ and $\sigma_z^2 = Var(\varepsilon^z_{t+1})$.

11 Appendix E: Data Construction

11.1 Data for Section 4: Cyclicality of Profits in Compustat

11.1.1 Macroeconomic Data

The GDP growth series is taken from Table 1.1.3 of the National Income and Product Accounts of the Bureau of Economic Analysis (`www.bea.gov`). Corporate profits (used in Table 1 only) are from the Table 1.12 (row 13: "Corporate profits with inventory valuation adjustment and capital consumption adjustment"). The real wage series and total factor productivity growth series are annualized, based on the quarterly seasonaly adjusted series from the Bureau of Labor Statistics Major Sector Productivity and Costs program (`www.bls.gov/lpc`). The series cover the nonfarm business sector. The series id that I use are PRS85006043 (real output), PRS85006033 (hours of all persons) and PRS85006153 (real hourly compensation). Following Arias, Hansen and Ohanian (2006), I compute TFP growth as $\Delta\log TFP = \Delta\log Y - 2/3 \times \Delta\log H$ where $\Delta\log Y$ is the real output series and $\Delta\log H$ is the hours of all persons series. For business cycle frequencies, taking into account capital does not affect the results. The real wage series is real hourly compensation (PRS85006153). This measure is based on the BEA estimates for labor compensation, and includes benefits. As a result, my real wage and productivity series are comparable in sectoral coverage and in construction.

11.1.2 Sample Construction in Compustat

I use annual Compustat data from 1963 to 2004. As is common, I exclude from the sample firms working in the financial sector or utilities (i.e. SIC between 6000 and 7000 or between 4900 and 5000). I keep only firms listed on the NYSE, the Nasdaq or the American Exchange. I drop observations with negative or missing sales (item 12) or assets (item 6). For the panel data regressions, I also exclude observations with negative operating income (item 13). I do not balance the panel. For the portfolio data, I follow the construction of Fama and French (1992, 1996). In particular, I follow their definition of book-to-market and their definitions of deciles based on the NYSE stocks.

11.1.3 Industry Controls

The industry controls are industry dummies and industry dummies interacted with GDP growth. The industries are the 30 industry classifications used by Fama and French (1997), which closely follow the 2-digit SIC codes. (See prof. French's website for the list of industries.)

11.2 Data for Section 5: Asset Pricing Factor Models

The return data is taken from prof. French's website. The consumption data is real consumption of non-durable goods and services, constructed from Tables 1.1.5 and 1.1.4 of the NIPA. The wage and productivity data are the same as above.

Correlation matrix	$\Delta \log GDP$	$\Delta \log TFP$	$\Delta \log w$	$\Delta \log \pi$
$\Delta \log GDP$	1			
$\Delta \log TFP$ (Total Factor Productivity)	0.87	1		
$\Delta \log w$ (Aggregate Real Wage)	0.24	0.42	1	
$\Delta \log \pi$ (Before-tax profits)	0.56	0.59	-0.12	1
Standard deviation	0.029	0.017	0.014	0.107
Standard deviation, relative to GDP	1	0.60	0.49	3.63
Regression coefficient on TFP growth	1.46	1	0.34	3.56

Table 1: Correlations and standard deviations of real GDP growth, total factor productivity (TFP) growth, real wage growth, and the growth rate of corporate profits before taxes. The last row gives the slope coefficient in a regression on TFP growth and a constant. The data are annual, 1947-2004, and are described in appendix E.

Correlation matrix	M/B	OI/S	EP
Market-to-Book (M/B)	1		
Operating Income over Sales (OI/S)	0.34	1	
Estimated Profitability (EP)	0.35	0.39	1

Table 2: Correlations between the three measures of idiosyncratic productivity. Each variable is normalized to have mean zero and cross-sectional standard deviation equal to one in each year. Compustat data, 1963-2004. 43,125 firm-year observations.

	β coeff. on Δ logGDP	γ coeff. on Δ logTFP	δ coeff. on Δ logWage
Operating Income	3.93 (0.14)	—	—
	—	4.87 (0.20)	-1.88 (0.26)
Net Income	5.20 (0.21)	—	—
	—	7.24 (0.31)	-3.44 (0.42)

Table 3: Pooled OLS regression of earnings growth (or net income growth) on GDP growth or on TFP growth and real wage growth. The equation estimated are $\Delta \log X_{i,t} = \alpha + \beta \Delta \log GDP_t + \varepsilon_{i,t}$ and $\Delta \log X_{i,t} = \alpha + \gamma \Delta \log TFP_t + \delta \Delta \log w_t + \varepsilon_{i,t}$, for X = earnings (item 13) or net income (item 172). The table reports β, γ and δ with the robust standard error in parenthesis. Compustat, 1963-2004. 43,125 firm-year observations, except for net income (32,796 firm-year observations).

Productivity Measure $x_{i,t}$	Industry controls	Coeff. δ_1	Std (δ_1)	Coeff. δ_2	Std (δ_2)
Market-to-Book	No	-1.71	0.23	1.23	0.29
	Yes	-1.23	0.24	0.84	0.31
Operating Income / Sales	No	-2.71	0.36	0.04	0.54
	Yes	-2.75	0.44	0.04	0.64
Profitability	No	-1.82	0.35	0.38	0.53
	Yes	-1.85	0.35	0.37	0.53

Table 4: Regression of Earnings Growth on TFP growth, real wage growth, and two interaction terms. The equation estimated is $\Delta \log OI_{i,t} = \alpha + \beta_1 \Delta \log TFP_t + \delta_1 x_{i,t-1} \Delta \log TFP_t + \beta_2 \Delta \log w_t + \delta_2 x_{i,t-1} \Delta \log w_t + \gamma_1 x_{i,t-1} + \gamma_2 \Delta \log K_{i,t} + \varepsilon_{i,t}$. OLS pooled regression. The table reports the point estimate for the two interactions terms δ_1 and δ_2, and the associated robust standard errors. Compustat data, 1963-2004. 43,125 observations. Earnings growth is the change in the logarithm of item 13, deflated by the CPI. The productivity measure is the current value in each year, for each firm.

Productivity Measure $\overline{x}_i$	Industry controls	Coeff. δ_1	Std (δ_1)	Coeff. δ_2	Std (δ_2)
Market-to-Book	No	-2.22	0.30	1.61	0.38
	Yes	-1.46	0.33	1.02	0.42
Operating Income / Sales	No	-2.18	0.32	0.30	0.46
	Yes	-2.06	0.46	0.41	0.67
Profitability	No	-1.05	0.42	0.58	0.64
	Yes	-1.01	0.42	0.55	0.64

Table 5: Regression of Earnings Growth on TFP growth, real wage growth, and two interaction terms. The equation estimated is $\Delta \log OI_{i,t} = \alpha + \beta_1 \Delta \log TFP_t + \delta_1 x_i \Delta \log TFP_t + \beta_2 \Delta \log w_t + \delta_2 x_i \Delta \log w_t + \gamma_1 x_i + \gamma_2 \Delta \log K_{i,t} + \varepsilon_{i,t}$. OLS pooled regression. The table reports the point estimate for the two interactions terms δ_1 and δ_2, and the associated robust standard errors. Compustat data, 1963-2004. 43,125 observations. Earnings growth is the change in the logarithm of item 13, deflated by the CPI. The productivity measure is the average over time for each firm.

Productivity Measure $\overline{x}_i$	Industry controls	Coefficient δ	Std (δ)
Market-to-Book	No	-1.65	0.20
	Yes	-1.09	0.22
Operating Income / Sales	No	-1.16	0.21
	Yes	-0.80	0.30
Profitability	No	-0.54	0.28
	Yes	-0.50	0.28

Table 6: Regression of Earnings Growth on GDP growth and an interaction term. The equation estimated is $\Delta \log OI_{i,t} = \alpha + \beta \Delta \log GDP_t + \delta x_i \Delta \log GDP_t + \gamma_1 x_i + \gamma_2 \Delta \log K_{i,t} + \varepsilon_{i,t}$. OLS pooled regression. The table reports the point estimate for the interaction term δ, and the associated robust standard error. Compustat data, 1963-2004. 43,125 observations. Earnings growth is the change in the logarithm of item 13, deflated by the CPI. The productivity measure is the average over time for each firm.

Productivity Measure $\overline{x}_i$	**Industry controls**	**Coeff.** δ	**Std** (δ)
Market-to-Book	No	-0.02	0.02
	Yes	-0.03	0.02
Operating Income / Sales	No	-0.09	0.02
	Yes	-0.06	0.04
Profitability	No	-0.10	0.030
	Yes	-0.12	0.03

Table 7: Test of the "fixed cost leverage". Regression of Earnings growth on Sales growth, the normalized productivity measure, and an interaction term. The equation estimated is $\Delta \log OI_{i,t} = \alpha + \beta \Delta \log S_{i,t} + \gamma x_i + \delta x_i \Delta \log S_{i,t} + \varepsilon_{i,t}$. The table reports the point estimate for the interaction term δ, and the associated robust standard error. Compustat data, 1963-2004. 43,125 firm-years observations. Earnings growth is the change in the logarithm of item 13, deflated by the CPI. The productivity measure is the average over time for each firm.

Productivity Measure $\overline{x}_i$	**Industry controls**	**Coeff.** δ_1	**Std** (δ_1)	**Coeff.** δ_2	**Std** (δ_2)
Market-to-Book	No	-3.04	0.46	2.17	0.62
	Yes	-2.15	0.51	1.46	0.71
Operating Income / Sales	No	-2.29	0.43	0.89	0.61
	Yes	-1.86	0.55	0.82	0.76
Profitability	No	-1.28	0.50	0.49	0.68
	Yes	-1.19	0.50	0.35	0.68

Table 8: Regression of Net Income Growth on TFP growth, real wage growth, and two interaction terms. The equation estimated is $\Delta \log NI_{i,t} = \alpha + \beta_1 \Delta \log TFP_t + \delta_1 x_i \Delta \log TFP_t + \beta_2 \Delta \log w_t + \delta_2 x_i \Delta \log w_t + \gamma_1 x_i + \gamma_2 \Delta \log K_{i,t} + \varepsilon_{i,t}$. The table reports the point estimate for the two interactions term δ_1 and δ_2, and the associated robust standard errors. Compustat data, 1963-2004. 32,796 firm-years observations. Net Income growth is the change in the logarithm of item 172, deflated by the CPI. The productivity measure is the average over time for each firm.

Productivity Measure $x_{i,t}$	**Industry controls**	**Coeff.** δ_1	**Std** (δ_1)	**Coeff.** δ_2	**Std** (δ_2)
Market-to-Book	No	-2.29	0.36	1.32	0.49
	Yes	-1.75	0.39	0.86	0.54
Operating Income / Sales	No	-2.96	0.45	1.54	0.62
	Yes	-2.99	0.57	1.76	0.75
Profitability	No	-2.00	0.45	1.26	0.62
	Yes	-2.07	0.45	1.21	0.63

Table 9: Regression of Net Income Growth on TFP growth, real wage growth, and two interaction terms. The equation estimated is $\Delta \log NI_{i,t} = \alpha + \beta_1 \Delta \log TFP_t + \delta_1 x_{i,t-1} \Delta \log TFP_t + \beta_2 \Delta \log w_t + \delta_2 x_{i,t-1} \Delta \log w_t + \gamma_1 x_{i,t-1} + \gamma_2 \Delta \log K_{i,t} + \varepsilon_{i,t}$. The table reports the point estimate for the two interactions term δ_1 and δ_2, and the associated robust standard errors. Compustat data, 1963-2004. 32,796 firm-years observations. Net Income growth is the change in the logarithm of item 172, deflated by the CPI. The productivity measure is the current value, in each year, for each firm.

	1	2	3	4	5	6	7	8	9	10
Operating Income/Sales	0.205	0.163	0.150	0.145	0.136	0.136	0.125	0.122	0.112	0.088
Operating Income/Assets	0.237	0.196	0.178	0.166	0.151	0.147	0.139	0.132	0.116	0.096
Book-to-Market	0.172	0.294	0.393	0.488	0.587	0.684	0.795	0.937	1.151	1.708

Table 10: Mean over time, for each portfolio, of the ratio of operating income to sales, the ratio of operating income to assets, and the book-to-market ratio. These are portfolios sorted by book-to-market. Portfolio 1 is the growth portfolio with low book-to-market and portfolio 10 is the value portfolio with a high book-to-market.

	1	2	3	4	5	6	7	8	9	10
Earnings										
coefficient	1.42	1.42	1.73	1.79	3.40	3.06	2.93	3.92	3.29	5.52
t-stat	3.42	2.72	1.85	2.87	5.10	6.64	4.21	4.73	5.39	7.20
R2	0.24	0.16	0.11	0.16	0.37	0.29	0.30	0.42	0.28	0.41
Net Income										
coefficient	1.79	2.75	3.06	2.67	6.28	7.49	6.88	9.26	17.97	na
t-stat	2.51	3.53	2.40	3.58	4.38	3.41	3.79	2.88	1.73	na
R2	0.20	0.32	0.20	0.20	0.36	0.41	0.42	0.31	0.19	na
Employment										
coefficient	0.86	1.23	0.84	1.40	1.34	1.20	1.30	1.37	1.17	1.69
t-stat	2.96	4.39	3.86	7.18	7.26	5.77	5.23	5.21	5.96	6.47
R2	0.10	0.30	0.20	0.49	0.49	0.28	0.42	0.39	0.32	0.49
Sales										
coefficient	0.81	0.93	0.78	0.60	1.25	1.14	1.46	1.32	1.28	2.39
t-stat	2.49	3.13	1.65	1.24	3.59	4.07	3.14	3.28	4.31	8.08
R2	0.08	0.18	0.07	0.05	0.20	0.18	0.19	0.20	0.20	0.44

Table 11: Regression of the change in the log of Operating Income (resp. Net Income, Employment, or Real Sales) on the change in the log of GDP, for each of the 10 portfolios sorted by book-to-market. Portfolio 1 is the growth portfolio with low book-to-market and portfolio 10 is the value portfolio with high book-to-market. The equation estimated is $\Delta \log Z_{i,t} = \alpha + \beta_i \Delta \log GDP_t + \varepsilon_{i,t}$, for Z=operating income, net income, employment, and sales. The table reports the coefficient on the change in the log of GDP, its t-statistic, and the R2 of the regression. The standard error is computed with the Newey-West formula with three lags. Note that $\Delta \log Z_{i,t}$ is the log of the sum of variable Z at time t+1 across all the firms that are in portfolio i at time t, minus the log of the sum of variable Z at time t across these same firms. Compustat data, 1963-2004. (Sample for net income: 1963-1991.) The coefficient on net income for portfolio 10 is not available because net income is negative for this portfolio in some years.

	1	2	3	4	5	6	7	8	9	10
Earnings regression										
coeff. on TFP growth	1.41	1.72	1.41	1.91	4.45	3.66	3.74	3.82	4.71	7.78
t-stat	2.65	3.20	1.92	2.13	3.88	4.05	4.13	4.62	4.26	5.62
coeff. on Wage growth	-0.21	-0.99	-0.45	-1.69	-2.22	-1.95	-2.27	0.66	-3.80	-4.42
t-stat	0.30	1.04	0.49	1.42	1.76	1.50	2.07	0.37	3.83	3.06
R2	0.14	0.11	0.04	0.09	0.31	0.20	0.23	0.30	0.28	0.39
Net Income regression										
coeff. on TFP growth	2.48	3.26	4.13	2.66	5.69	8.35	8.56	10.92	22.81	na
t-stat	3.68	3.76	2.04	2.29	2.89	2.89	4.37	2.65	1.95	na
coeff. on Wage growth	-1.86	-0.78	-4.63	-0.96	-0.03	-3.86	-5.84	-8.28	-20.00	na
t-stat	1.81	0.43	1.61	0.51	0.01	1.30	2.35	1.93	1.99	na
R2	0.17	0.24	0.18	0.10	0.18	0.24	0.29	0.19	0.14	na

Table 12: Regression of the change in the log of Operating Income (resp. Net Income), on the change in the log of TFP and the change in the log of the aggregate real wage, for each of the 10 portfolios sorted by book-to-market. Portfolio 1 is the growth portfolio with low book-to-market and portfolio 10 is the value portfolio with a high book-to-market. The equation estimated is $\Delta \log OI_{i,t} = \alpha_i + \beta_i \Delta \log TFP_t + \gamma_i \Delta \log w_t + \varepsilon_{i,t}$. The table reports the coefficient on the change in the log of GDP, its t-statistic, and the R2 of the regression. The standard error is computed with the Newey-West formula with three lags. Note that $\Delta \log Z_{i,t}$ is the log of the sum of variable Z at time t+1 across all the firms that are in portfolio i at time t, minus the log of the sum of variable Z at time t across these same firms. Compustat data, 1963-2004. (Sample for net income: 1963-1991.) The coefficient on net income for portfolio 10 is not available because net income is negative for this portfolio in some years.

	1 (Low)	2	3	4	5 (High)	HML
1 (Small)	0.96	2.51	2.60	3.34	3.54	2.59
2	1.30	2.23	2.78	2.99	3.20	1.91
3	1.65	2.33	2.37	2.78	3.07	1.42
4	1.80	1.80	2.47	2.60	2.75	0.95
5 (Big)	1.61	1.65	1.91	1.90	2.04	0.43
SMB	-0.66	0.87	0.70	1.44	1.50	

Table 13: Mean quarterly excess return on the 25 portfolios sorted by size and book-to-market of Fama and French (1996). Data is quarterly from 1952-I to 2002-IV. The last column reports the difference between the columns five and one, and the last row reports the difference between the rows five and one.

	1 (Low)	2	3	4	5 (High)	HML
1 (Small)	371.70	323.25	303.35	320.94	371.05	-0.65
std	(127.08)	(111.70)	(100.20)	(89.18)	(88.97)	(72.08)
2	292.42	251.64	254.26	316.26	328.32	35.90
std	(108.40)	(95.30)	(78.87)	(75.39)	(83.52)	(64.62)
3	197.36	254.61	248.30	292.83	293.25	95.89
std	(98.10)	(75.66)	(74.27)	(69.59)	(73.92)	(61.76)
4	171.42	210.92	237.83	292.64	317.00	145.58
std	(83.57)	(68.03)	(61.15)	(64.21)	(91.44)	(64.29)
5 (Big)	163.83	174.48	199.91	232.16	260.63	96.80
std	(65.04)	(53.60)	(54.78)	(57.29)	(78.49)	(68.54)
SMB	207.87	148.77	103.43	88.78	110.42	
std	(86.87)	(77.51)	(75.14)	(56.57)	(59.79)	

Table 14: Beta on TFP growth, and the associated standard error, for each of the 25 portfolios sorted by size and book-to-market of Fama and French (1996). Data is quarterly from 1952-I to 2002-IV.

	1 (Low)	2	3	4	5 (High)	HML(size)
1 (Small)	284.46	252.16	104.78	104.11	67.67	-216.80
std	(183.14)	(157.25)	(123.70)	(119.21)	(129.60)	(122.20)
2	274.38	182.65	200.24	119.67	126.84	-147.54
std	(157.95)	(130.54)	(110.76)	(103.88)	(122.05)	(108.93)
3	408.75	148.02	154.52	155.23	103.78	-304.97
std	(156.78)	(106.95)	(101.80)	(104.35)	(113.36)	(117.75)
4	378.58	169.70	148.31	157.86	95.72	-282.85
std	(155.09)	(105.60)	(99.74)	(88.89)	(98.82)	(108.98)
5 (Big)	329.39	194.00	79.82	138.90	155.68	-173.71
std	(120.42)	(99.98)	(83.93)	(94.31)	(94.97)	(89.31)
SMB(value)	-44.93	58.16	24.96	-34.79	-88.01	
std	(129.71)	(113.82)	(86.68)	(82.55)	(83.99)	

Table 15: Beta on wage growth, and the associated standard error, for each of the 25 portfolios sorted by size and book-to-market of Fama and French (1996). Data is quarterly from 1952-I to 2002-IV.

	1st stage		2nd stage	
	TFP factor	Wage factor	TFP factor	Wage factor
b	108.52	-90.85	105.17	-96.80
$\sigma(b)$	35.64	81.70	21.23	32.24
J-test and p-val	21.377	(0.558)		
λ	0.009	-0.003	0.009	-0.003
$\sigma(\lambda)$	0.003	0.003	0.002	0.001
MAE	0.369		0.424	

Table 16: Estimation results for the productivity-wage factor model on the 25 Fama-French portfolios. b is the loading on each factor, and lambda is the price of risk for each factor. The J-test is Hansen's (1982) test of overidentifying restrictions. MAE is the mean absolute pricing error error, in percent per quarter.

	CCAPM		CAPM	
	1st stage	2nd stage	1st stage	2nd stage
b	243.78	195.95	0.029	0.035
$\sigma(b)$	103.56	42.68	0.009	0.006
J-test and p-val	19.168	(0.743)	21.290	(0.622)
λ	0.008	0.006	2.042	2.431
$\sigma(\lambda)$	0.003	0.001	0.648	0.442
MAE	0.555	0.763	0.694	0.676

Table 17: Estimation results for the CCAPM and CAPM models respectively on the 25 Fama-French portfolios. b is the loading on each factor, and lambda is the price of risk for each factor. The J-test is Hansen's (1982) test of overidentifying restrictions. MAE is the mean absolute pricing error, in percent per quarter.

Fama-French three factor Model	1st stage			2nd stage		
	SMB	HML	RMRF	SMB	HML	RMRF
b	-0.001	0.067	0.038	-0.001	0.067	0.039
$\sigma(b)$	0.018	0.019	0.012	0.013	0.012	0.010
J-test (p-val)	21.152	(0.511)				
λ	0.577	1.579	1.637	0.582	1.595	1.655
$\sigma(\lambda)$	0.495	0.583	0.655	0.325	0.386	0.554
MAE	0.288			0.285		

Table 18: Estimation results for the Fama-French three factor model on the 25 Fama-French portfolios. b is the loading on each factor, and lambda is the price of risk for each factor. The J-test is Hansen's (1982) test of overidentifying restrictions. MAE is the mean absolute pricing error, in percent per quarter.

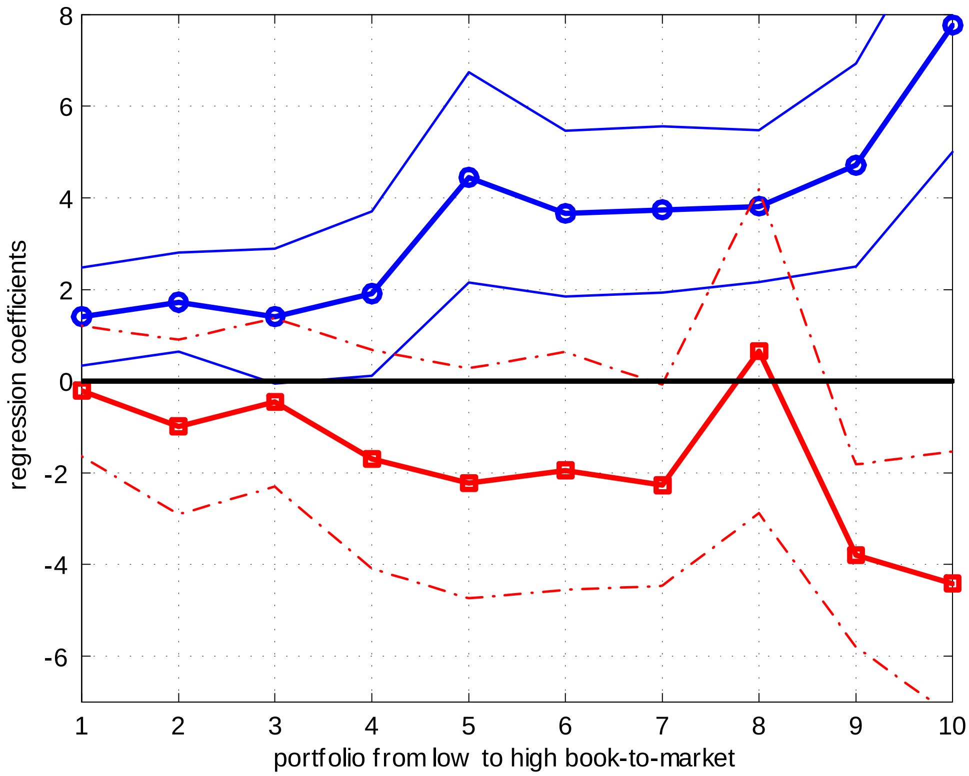

Figure 1: This figure plots the estimates β_i (circles) and γ_i (squares) from the regression $\Delta \log OI_{i,t} = \alpha_i + \beta_i \Delta \log TFP_t + \gamma_i \Delta \log w_t + \varepsilon_{i,t}$, for each of the ten book-to-market sorted portfolios, with the associated plus and minus two-standard deviation bands. Portfolio 1 is the growth portfolio with low book-to-market and portfolio 10 is the value portfolio with high book-to-market. This a graphical representation of the rows 1 and 3 of Table 12. The standard errors are computed with the Newey-West correction with three lags. Compustat, annual data, 1963 to 2004.

FIGURES

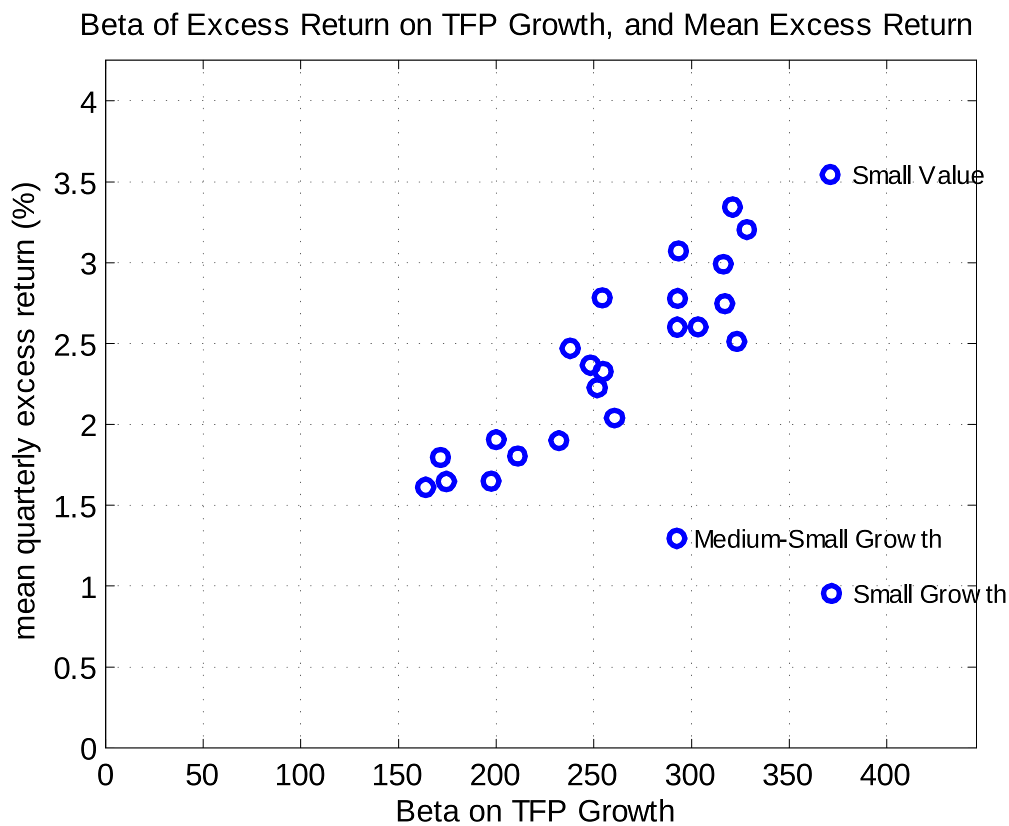

Figure 2: This figure plots the beta of the excess return on the productivity factor, against the mean excess return, for each of the 25 Fama-French portfolios sorted by size and book-to-market. The productivity factor is total factor productivity (TFP) growth. The beta is obtained for each portfolio by a time-series regression of excess return on the two factors (TFP growth and wage growth) and an intercept. The data is quarterly from 1952-I to 2002-IV.

Figure 3: This figure plots the beta of the excess return on the wage factor, against the mean excess return, for each of the 25 Fama-French portfolios sorted by size and book-to-market. The wage factor is aggregate real wage growth. The beta is obtained for each portfolio by a time-series regression of excess return on the two factors (TFP growth and wage growth) and an intercept. The data is quarterly from 1952-I to 2002-IV.

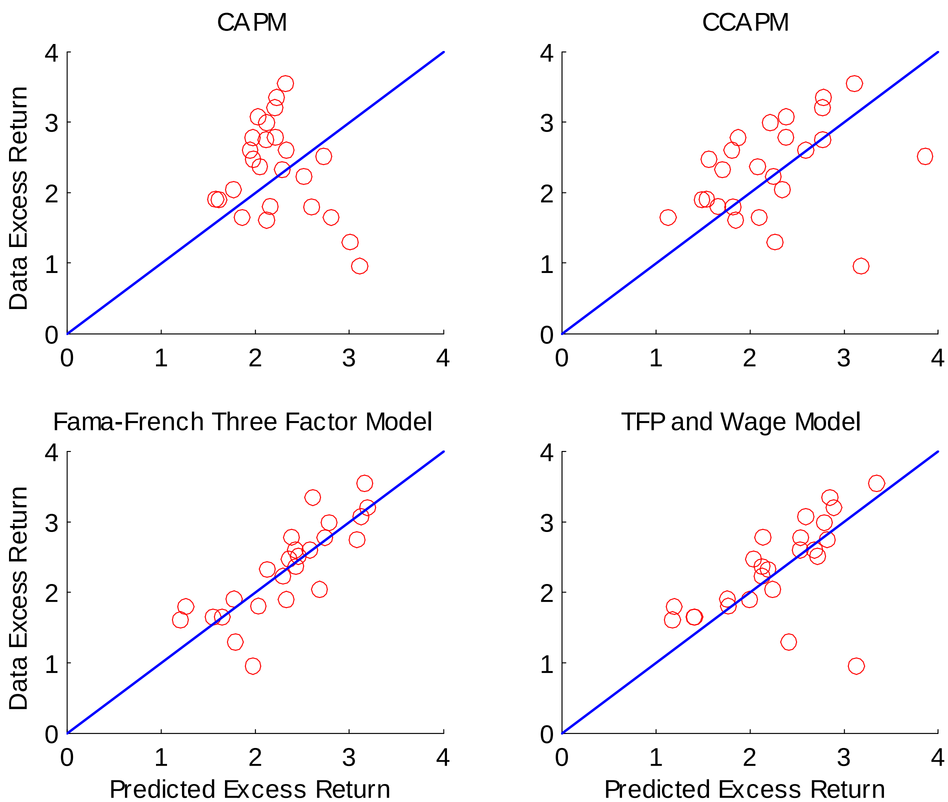

Figure 4: This figure plots the data mean excess return and the predicted excess return, for each of the 25 Fama-French portfolios, sorted by size and book-to-market, and for each of four models: the CAPM (top left panel), the CCAPM (top right panel), the Fama-French three factor model (bottom left panel), and the productivity (TFP) and wage model of this paper. The units are percent per quarter. The blue line is the 45-degree line. The data is quarterly from 1952-I to 2002-IV. See section 5 for details.