# ESSAYS on Macroeconomic Risks and Stock Returns

by

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# ABSTRACT


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Essay1: We use two dynamic factors, one real and the other nominal, to summarize the systematic information. We then separate the cash flow effect from the pricing kernel effect by linking systematic economic risks to stock returns. We show that the market charges a positive price for the real output growth risk, but a negative price for the inflation risk.

Essay2: We estimate the conditional covariances between excess returns on a large cross section of stock portfolios and the economic shocks. The system of equations are estimated with a common slope coefficient between excess returns and their conditional covariance with the economic shocks. The results indicate a significantly negative (positive) relation between the portfolio returns and their conditional covariance with the inflation-related (output-related) shocks.

Essay3: Economic theory suggests that a company's currency risk exposure depends crucially on its fundamental involvement in international trade. For US industries, we find that the stock performance of an import-oriented company moves positively with the performance of the dollar, but the stock performance of export-oriented company tends to move against the dollar.

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# Part I

# Market Pricing of Economic Risks and Stock Returns

## 1.1. Introduction

Fundamentally, financial security valuation should be linked to the systematic states of the aggregate economy. On the one hand, real output growth directly governs the aggregate consumption growth in an economy, a key determinant of the real pricing kernel in classic asset pricing models (Merton (1973), Ross (1976), Lucas (1978), and Breeden (1979)). On the other hand, inflation not only directly affects the nominal pricing kernel, but it can also enter the real side of the pricing kernel via its dynamic interactions with the real production (Piazzesi and Schneider (2006)). Quantifying these linkages has paramount importance in understanding and developing economic and asset pricing theories. Yet, despite several decades of empirical effort in measuring the relation between economic risks and stock returns,[1] empirical support from the literature has been far and few. Researchers who have tried to link the pricing of macroeconomic risks to stock returns have been facing several significant challenges.

First, many macroeconomic indicators are available. Each indicator contains some information, but also a tremendous amount of noise, about the systematic state of the economy. Directly incorporating a noisy economic indicator as a regressor suffers from the well-known errors-in-variable problem. The coefficient estimates can be significantly biased toward zero by the large noise. Furthermore, since the movements of most economic

[1] The list of studies is long and ever growing. Prominent examples include Bodie (1976), Fama and Schwert (1977), Castanias (1979), Fama (1981, 1990), Geske and Roll (1983), Pearce and Roley (1983, 1985), Rozeff (1984), Chen, Roll, and Ross (1986), Keim and Stambaugh (1986), Campbell (1987), Campbell and Shiller (1988), Cutler, Poterba, and Summers (1989), Fama and French (1988, 1999), Ross (1989), Schwert (1990), Shanken and Weinstein (1990), Chen (1991), Ferson and Harvey (1991), Chan, Karceski, and Lakonishok (1998), and Flannery and Protopapadakis (2002).

indicators are highly correlated, the regression coefficient estimate on an indicator depends crucially on what other economic indicators are included in the same regression. Besides, including too many highly correlated indicators into a regression can also lead to stability and multicollinearity issues, as the real dimension of the aggregate economy is much smaller than the number of available economic indicators. Therefore, how to extract the systematic movements in an economy from the many noisy series poses the first challenge.

Second, the systematic states of the aggregate economy influence the valuation of a stock not only through their linkages to the aggregate pricing kernel, but also through their impacts on the cash flows entitled to the equity owners of the company. The cash flow effect varies with the nature of the company's business. A pro-cyclical company tends to have higher earnings during booming economies than during recessions. A countercyclical company tends to show the opposite effect. By contrast, the pricing kernel effect is a market-wide effect that affects all financial security valuations. To exclude arbitrage, one pricing kernel should apply to the valuation of all financial securities. Therefore, how to separate the company-specific cash flow effect from the market's equilibrium pricing of economic risks presents the second challenge.

In this paper, we address the first challenge by using a dynamic factor model approach. We use two dynamic economic factors to summarize the fundamental information about the real and nominal states of the economy from the numerous noisy macroeconomic indicators. The dynamic factor model provides an effective way of suppressing noise and highlighting the information content in the many noisy series. We use maximum likelihood estimation joint with Kalman (1960) filter to identify the dynamic factors from a large array of macroeconomic indicators. The estimation also identifies the dynamic interactions between the two fundamental dimensions of the aggregate economy.

To address the second challenge, we propose a two-step procedure. In the first step, we regress returns on each stock on innovations in the two economic factors. The relative difference of the regression coefficients across different stocks reveals the difference in their respective cash flow exposures to the two economic factors. In the second step, we study how the expected return on a stock or a stock portfolio varies with its exposures to the economic risks. The variation reveals how the market prices the economic risk exposures. If investors do not price an economic risk, the expected stock returns will not vary with the stock's exposure to the economic risk. On the other hand, a positive coefficient estimate would suggest that investors dislike positive exposures to the economic risk and ask for a higher expected return for bearing the risk. A negative coefficient would suggest that investors are willing to accept a lower expected return to gain positive exposure to the risk, possibly because the exposure generates some beneficial effects on one's utility.

The first-stage regression generates risk exposure estimates that vary greatly across stocks. A one standard deviation positive shock on the inflation risk can move some stocks up by 14.76% per month while moving some other stocks down by 12.13% per month. Similarly, a one standard deviation positive shock on the real output growth risk can drive some stocks up by 16.55% per month, while driving some other stocks down by 34.26% per month. By contrast, if we regress the market portfolio return on the two economic risks, as sometimes done in the literature, the average market response is merely $-0.48\%$ per month per one standard deviation shock on the inflation risk and $-0.26\%$ per month per one standard deviation shock on the real output growth risk. The latter estimate is not statistically significant. These statistics suggest that exploiting the cross-sectional variation in risk exposures is important not only for controlling for the cash flow effect, but also for enhancing the statistical power of the market price identification.

When we aggregate the economic risk exposure over then industries, we find that the consumer durables industry shows the highest positive exposure to the real output growth factor, an indication that the industry is pro-cyclical on average. By contrast, the health care, medical equipment, and drugs industry shows the largest negative exposure to the real output growth factor, and indication that the industry is on average counter-cyclical. On the other hand, the average inflation exposures on all ten industries are negative, with the exposure most negative on the health care industry and least negative on the energy industry.

To determine the market prices of the two economic risks, we analyze how the expected returns on different stocks vary with their economic risk exposures. First, we form 100 stock portfolios based on their ranking in risk exposures to the two economic risk factors. We compare the average returns for the ranked portfolios, and find that portfolios with high positive exposure to inflation factor have lower average returns and portfolios with high positive exposure to real factor have higher average returns. The average return spread between the highest and the lowest real output growth beta portfolios is $0.19\%$ per month with a $t$-value of 1.81, and the average return spread between the highest and the lowest inflation beta portfolios is $-0.30\%$ per month, with a $t$-value of 2.39.

Second, at each period, we regress cross-sectionally next period's return on each stock against its current exposure estimates on the two economic shocks. The slope coefficients measure how the expected returns on stocks vary linearly with the economic risk exposures. We average the cross-sectional regression coefficients over time to determine the average risk premium induced by exposure to each economic risk. We find that the average coefficient on the inflation risk is negative, but that on the real output growth risk is positive. Thus, stocks that have negative exposure to the inflation risk and positive exposure to the real output growth risk have higher expected returns on average. One standard deviation cross-sectional variation in the inflation risk exposure leads to an expected return difference of $-0.19\%$ per month. One standard deviation variation in the real output growth risk exposure leads to an expected return difference of $0.27\%$ per month.

The results from the two estimation methods lead to the same conclusions on the market pricing of economic risks. The positive market price for the real output growth risk provides empirical support for classic asset pricing theories that argue for consumption smoothing. Intuitively, payoffs from a cyclical company work against real consumption smoothing and hence generate lower valuation and higher expected returns. The opposite is true for counter-cyclical companies.

The negative market price on the inflation risk suggests that inflation not only affects the nominal stock return, but also enters the real side of the pricing kernel, potentially due to dynamic interactions between inflation and real output growth. Our estimated economic factor dynamics suggest that inflation and real output growth not only show negative contemporaneous correlations, but they can also dynamically predict each other. In particular, high inflation predicts future slowing down in real output growth, whereas high real growth can generate high future inflation. As a result, stocks with high positive correlations with the inflation factor can play a hedging role against future real consumption risks. Investors are willing to accept a lower expected return for the hedging benefit.

In an influential paper, Campbell and Vuolteenaho (2004) break the beta of a stock with the market portfolio into two components, one reflecting news about the market's future cash flows (bad beta) and one reflecting news about the market's discount rates (good beta). Here, we decompose the aggregate economy into two fundamental dimensions: the real output growth and inflation. The two risk dimensions enter both the cash flows and the discount rates. The real output growth shows mainly a cash flow effect. A positive shock on the real output growth predicts positively on future cash flows and hence generates a "bad beta". In some monetary policy rules such as the famous Taylor (1993) rule, a positive shock on the real output growth also partially increases the short-term nominal interest rate, but this influence becomes smaller as the central bank emphasizes more on inflation targeting. On the other hand, a positive shock on inflation predicts negatively on future real cash flow growth. Furthermore, under most policy rules, the nominal short rate increases more than proportionately to increases in expected inflation. Therefore, both the negative cash flow effect and the positive discount rate effect from a positive inflation generates a "good beta" and hence a negative premium.

Compared to the long list of studies that attempt to understand how economic risks are priced in stock returns, we make two major contributions. First, rather than picking one or a few noisy economic indicators to proxy inflation or output growth, or interpreting each series in a stand-alone basis, we employ a dynamic factor model approach and use two dynamic factors to summarize the systematic information and to suppress the idiosyncratic noise in a large array of macroeconomic indicators. The high information content in the two dynamic economic factors enables us to identify the risk exposures in stock returns more accurately and reduces our chance of misidentification and misinterpretation induced by the large noisy content in a single series and the potential multi-collinearity issue when multiple economic series are included in a regression.

Our second contribution lies in our careful separation of the pricing kernel effect from the cash flow effect by exploiting the large cross section of individual stocks. Existing studies often focus on the market portfolio return and analyze its relation with economic variables. Depending on the nature of a company, its cash flow can either move positively or negatively with the economic conditions. Different cash flow dependence leads to different relations between stock returns and the economic shocks. Narrowly focusing on the market portfolio return amounts to averaging these different relations. Thus, it is not surprising that such exercises often generate results that are either insignificant or difficult to interpret. In this paper, by first estimating the risk exposure at the firm level and then form portfolios based on their exposure ranks, we can exploit the cross-sectional information to control for the cash flow effect and to highlight how the expected returns vary with the estimated economic risk exposures.

The rest of the paper is organized as follows. Section 1.2 describes the literature that forms the background of our study. Section 1.3 describes the procedure for extracting the dynamic economic factors from a wide array of macroeconomic indicators. Section 1.4 estimates the economic risk exposures for each individual firms. Section 1.5 estimates the risk premium for each of the two economic risk exposures. Section 1.6 concludes.

## 1.2. Background

Existing studies on the relation between economic risks and stock returns often focus on the contemporaneous relation between the aggregate market returns and innovations in economic indicators. Bodie (1976), Fama (1981), Geske and Roll (1983), and Pearce and Roley (1983, 1985) find a negative impact of inflation on equity values.

Flannery and Protopapadakis (2002) estimate a GARCH model of daily market returns, in which realized returns and their conditional volatility depend on 17 macroeconomic announcement series. From the 17 series, they identify six priced factors. As we have discussed earlier, directly incorporating economic indicators into a regression analysis suffer severely from errors-in-variable problems and potentially multi-collinearity issues when many series are included in the same regression.

In a cross-sectional analysis, Chen, Roll, and Ross (1986) find weak evidence that supports inflation as a priced risk factor. Nevertheless, Shanken and Weinstein (1990) show that the conclusion depends on the specific method used to form testing portfolios. Correcting for errors-in-variables further reduces the statistical importance of macro factors for equity returns.

Cutler, Poterba, and Summers (1989) find that industrial production growth is significantly positively correlated with real stock returns over the period 1926-1986, but not in the 1946-1985 subperiod. They find no support for the hypothesis that inflation reliably affects stock returns.

In time-series analysis, Fama and Schwert (1977), Rozeff (1984), Keim and Stambaugh (1986), Campbell (1987), Campbell and Shiller (1988), and Fama and French (1988, 1999) find that expected inflation can predict the expected returns of stocks.

On the theoretical side, stocks have long been considered as an inflation hedge because stock represents ownership of physical capital whose real value is assumed to be independent of the rate of inflation (Linter (1973), and Bodie (1976)). Fama (1981) argues that the negative contemporaneous stock return-inflation relation identified in some studies is induced by a negative relation between inflation and real activity. He attributes the negative real-normal interaction to a combination of money demand theory and the quantity theory of money.

## 1.3. Extracting Dynamic Economic Factors

The basic approach taken in previous empirical studies has been to regress stock market portfolio returns on a group of economic indicators that proxy for inflation and/or real economic activity. This practice is likely to generate unreliable results due to its inherent econometric defects. First, the large noise and measurement errors in most economic indicators bias the regression coefficients toward zero due to the well-known errors-in-variable issue. Second, since the values of most economic indicators are highly correlated, the regression coefficients vary with the set of economic indicators included in the regression. Including too many highly correlated indicators into one regression can also lead to stability and multi-collinearity issues, as the real dimension of the economy is much smaller than the number of available economic indicators. To resolve these empirical challenges, we use a dynamic factor model to succinctly summarize the information and suppress the noise in many macroeconomic indicators.

### 1.3.1. Extracting dynamic factors from macroeconomic indicators using Kalman filter

Early studies by Sargent and Sims (1977), Sargent (1989), and Stock and Waston (1989) suggest that a small number of factors can account for much of observed variation in major economic aggregates. Broadly speaking, we can decompose the aggregate economy into two fundamental dimensions: (1) the nominal side of the economy, which we call inflation, and (2) the real side of the economy which we call real output growth. The numerous economic indicators all reveal to some extent the real and nominal states of the economy, but they also all contain a large amount of noise, either due to measurement errors or due to the idiosyncratic feature of the indicator definition.

Formally, we use $X_t \equiv [\pi_t, g_t]^\top$ to denote the vector of the two economic risk factors: inflation ($\pi$) and real output growth ($g$). We assume the following dynamics on the economic risk factors:

$$X_t = \Phi X_{t-1} + \varepsilon_t, \quad Q = \mathbb{E}[\varepsilon_t \varepsilon_t^\top], \tag{1.1}$$

where $\Phi$ denotes the autocorrelation matrix that measures the dynamic interactions between the inflation and real output growth factors, and $\varepsilon_t$ denotes the innovation vector, which we assume normally distributed with zero mean and covariance matrix $Q$. For identification, we normalize the economic factors to have zero unconditional mean, and the innovation vector to have unit variance.

We use $M_t \in \mathbb{R}^N$ to denote a large array ($N$) of economic indicators, with the number of economic indicators much larger than the actual economic risk dimensions. We summarize the systematic movements underlying these economic indicators through the following linear factor structure,

$$M_t \;=\; HX_t + e_t, \quad \text{with } R = \mathbb{E}[e_t e_t^\top], \tag{1.2}$$

where the macroeconomic series $M_t$ are demeaned before we relate them to the economic factors, $H$ is an $(N \times 2)$ matrix of factor loading coefficients, and $e_t$ denotes an $(N \times 1)$ vector of measurement errors, with $R$ denoting its covariance matrix. For model estimation, we assume that the measurement errors are independent of the state vector, and that they are also mutually independent, but with distant variance for each series, reflecting the different degrees of noise level in each series.

If we regard the state vector dynamics in (1.1) as our state-propagation equation and their relation to the macroeconomic series in equation (1.2) as the measurement equation, we can use Kalman filter to predict and update the economic factors from the large array of economic observations. Specifically, let $\overline{X}_t$, $\overline{V}_t$, $\overline{M}_t$ and $\overline{A}_t$ denote the time-$(t-1)$ ex ante forecast of time-$t$ values of the state vector, its covariance matrix, the measurement series, and their covariance matrix. Let $\hat{X}_t$ and $\hat{V}_t$ denote the ex post update or filtering on the state vector and its covariance at time $t$ based on time-$t$ economic observations $M_t$. The Kalman filter provides the efficient updates on these quantities. The predictions are,

$$\begin{aligned} \overline{X}_t &= \Phi\widehat{X}_{t-1}, \quad \overline{V}_t = \Phi\widehat{V}_{t-1}\Phi^\top + Q, \\ \overline{M}_t &= H\overline{X}_t, \qquad \overline{A}_t = H\overline{V}_t H^\top + R. \end{aligned} \tag{1.3}$$

The updates are,

$$\widehat{X}_t = \overline{X}_t + K_t(M_t - \overline{M}_t), \quad \widehat{V}_t = \widehat{V}_t - K_t\overline{A}_t K_t^\top, \tag{1.4}$$

with $K_t = \overline{V}_t H^\top(\overline{A}_t^{\,-1})$ denoting the Kalman gain. Innovations (shocks) in the systematic economic risk factors at each time period $t$ are measured by the difference between the ex post updates and the ex ante forecasts on the two economic factors: $ES_t = \widehat{X}_t - \overline{X}_t$.

Given the Kalman filter predictions and updates, we define the likelihood function on the forecasting errors of the macroeconomic series:

$$\mathcal{L}(\Theta) = -\frac{1}{2}\sum_{t=1}^{T}\left[\log|\overline{A}_{t+1}| - \frac{1}{2}\left((M_{t+1} - \overline{M}_{t+1})^\top(\overline{A}_{t+1}^{\,-1})(M_{t+1} - \overline{M}_{t+1})\right)\right] \tag{1.5}$$

where $T$ denotes the number of observations for each series. We maximize the likelihood values to obtain the structural parameters $[\Phi, H, Q, R]$ that determine the economic risk dynamics and the relations of each economic series to the economic risk factors. In related literature, Engle and Watson (1981), Stock and Waston (1989, 1991), Quah and Sargent (1993), and Clayton-Matthews and Crone (2003) have used the maximum likelihood method with Kalman filter successfully in estimating dynamic economic factors.

### 1.3.2. Data description

Our estimation is based on 11 monthly or quarterly macroeconomic series spanning the period January 1953 to December 2005. The data are from the Federal Reserve Board. They include seven inflation-related series: the consumer price index (CPI), the core CPI, the producer price index (PPI), the core PPI, the personal consumption expenditure (PCE) deflator, the core PCE deflator, and the gross domestic production (GDP) deflator. The GDP deflator is available in quarterly frequency. All other variables are available in monthly frequency. We first convert the price indexes into year-over-year percentage changes, and then standardize each series by subtracting the sample mean and dividing the series by the sample standard deviation.

The CPI measures the average change in the prices of a basket of goods and services bought by a typical urban household. The PPI measures the change in the selling prices received by domestic producers for all finished goods. The PCE deflator measures the average change in the prices of a basket of goods and services purchased by the typical consumer such as individuals and non-profit organizations. Their respective core measures exclude food and energy, the prices of which tend to be highly volatile. The GDP deflator measures the average change in the prices of all goods and services produced by the domestic economy.

Among the seven inflation measures, the CPI is the most cited inflation measures, but the price changes at the wholesale level, as captured by the PPI numbers, are often passed through to the consumer price index in a later date. Hence, tracking prices from the PPI numbers, investors can anticipate inflationary consequences in the coming months. On the other hand, the PCE deflator is becoming the most watched price index from the standpoint of monetary policy and is considered as a "more reliable measure of inflation by the Federal Reserve" for two reasons.[2] First, the PCE deflator is a broader measure that covers both urban and rural customers. By contrast, the CPI is only representative of the price paid by urban customers. Second, the PCE deflator is a chain-weighted index that captures shifting spending patterns, but the CPI is a fixed-weight index that relies on spending patterns several years ago. Each of the above three indices has a corresponding core measure that excludes food and energy. Many economists and investors prefer the core measures because they think that shocks to energy prices are often transitory. Others disagree. Finally, since the GDP deflator includes all goods and services produced by the domestic economy, it is the most comprehensive measure of inflation. However, the GDP deflator is released quarterly while all other inflation measures are released monthly. In

[2]Quotes are from the testimony of Alan Greenspan before the Committee on Financial Services, U.S. House of Representatives, July 18, 2001.

our application, we do not take a stand on which of the seven series provides the most accurate and timely measure of the inflationary pressure. Instead, we include all of them into our estimation and extract one common factor (and its stochastic trend) that captures the systematic movements in inflation pressure.

The data set also includes four series on real activity: the real GDP, industrial production, non-farm payrolls, and the real PCE. The real GDP is available in quarterly frequency. The other three series are available in monthly frequency, but the data on real PCE start at a later date in January 1991. The real GDP growth is the broadest measure of the output growth of the domestic economy. Industrial production measures the production of goods. Although it is less comprehensive, it is more timely since the industrial production numbers are released monthly whereas the GDP numbers are released quarterly. Non-farm payrolls measure the number of employees on firm's payrolls. Farms are excluded because of their seasonal nature, which can skew total employment figures. This number is a key indicator of the employment scenario of the economy, which has far-reaching implications for both inflation and output growth. On the demand side of the economy, we include real personal consumption expenditure, which often indicates changes in the state of the economy prior to changes in production. Again, we first turn the four series into year-over-year growth rates and then standardize them before we extract the real growth factor and its stochastic trend.

Table 1.1 reports summary statistics of each of the 11 macroeconomic series, as well as their sampling frequency, starting date, and number of observations. The autocorrelation statistics are computed on their respective data frequencies, either monthly or quarterly. Seven of the 11 series are available at the start of our sample (January 1953). The remaning five series start at a later date. The average inflation varies with the definitions, but all seven measures generate sample averages around 3-4% per annum. The three real output measures also generate growth rates around 3-4% per annum. The non-farm payoffs grow at an average pace of about 2% per annum. Over our sample period, the highest inflation estimate is 19.492% from PPI, and the lowest estimate is also from PPI at -2.823%. These statistics and the standard deviation estimates indicate that the PPI is the most volatile inflation measure. On the real side of the economy, the most volatile is the industrial production, which has a standard deviation estimate more than twice as much as the standard deviation estimates on the other two measures.

We extract the dynamic factors in monthly frequency. For data series that are available in quarterly frequency or at a later date, we fill the series with missing values. Our estimation method readily accommodates missing data. At each month, we update the dynamic factors based on the available subset of the data.

### 1.3.3. The information content of economic indicators

Table 2.1 report the estimates and the $t$-statistics (in parentheses) of parameters ($H$) that link each economic series to the two systematic dynamic factors. In principle, factors can rotate and the loadings can change accordingly without impacting the final result. However, such rotations make it difficult to interpret the economic meanings of the dynamic factors.

To improve identification and enhance the economic interpretation of the factors, we put structural constraints on the factor loading matrix. We constrain the inflation factor $\pi_t$ to have positive loadings on the seven inflation series and the non-farm payroll series, and zero loadings on all other series. We constrain the real output growth factor $g_t$ to have nonzero loadings only on real GDP, industrial production, non-farm payroll, and the real component of the personal consumption expenditure.

Entries under $R$ report the measurement error variance estimates and $t$-statistics for each series. The last column reports the predicted variation of the factors on each series, defined as one minus the ratio of the forecasting error variance over the variance of the original series. Since each series is standardized to have a unit unconditional variance, the measurement error variance reflects the relative goodness of fit for each macroeconomic series. Similarly, the predicted variation measures the predictive performance of the two dynamic factors on each of the 11 series. It also reflects the relative informativeness of 11 series in terms of their affinity to the extracted economic factors.

Among the seven inflation series, the highest predicted variation comes from PCE deflator, consistent with the Federal Reserve's emphasis on this measure as a more reliable gauge of the inflation pressure. The lowest predicted variation comes from PPI, which is also the most volatile series. Nevertheless, the loading estimates on all seven inflation series are statistically significant and positive, suggesting that all seven measures contain useful information about the state of inflation. Hence, it is appropriate to use them all instead of picking one against the others.

The non-farm payroll number is a key indicator of the employment scenario of the economy. It has far-reaching implications for both inflation and output growth. The loading estimate on the inflation factor is smaller than those on the seven inflation series, but the high $t$-statistic suggests that this loading estimate is strongly significant and that non-farm payrolls are informative about the inflation pressure of the economy.

Among the four output and employment series, non-farm payrolls also have the highest $t$-statistics for its loading on the real output growth factor. Furthermore, the predicted variation is higher than those from the three output series, showing that the non-farm payrolls series is very informative about the economy. Again, however, all four series have significantly positive loadings on the real output growth factor. Hence, they are all informative about the real side of the economy.

### 1.3.4. The dynamic interactions between nominal and real economic risks

Table 2.2 reports the estimates of the parameters that control the dynamics of the two economic factors. The matrix $\Phi$ measures the persistence of the two economic risk factors and their dynamic interactions. The diagonal elements show that the inflation factor is more persistent than the real output growth factor. The first diagonal element is greater than one, but the factor dynamics remain stationary due to the interactions between the two factors. The real parts of the two eigenvalues of the matrix are equal at 0.9885. The off-diagonal estimate in the first column is $-0.0183$, suggesting that the inflation factor negatively predicts the real output growth factor. High inflation is likely to lead to future recession. The off-diagonal element estimate in the second column is 0.0568, indicating that real output growth can also affect future inflation. The positive estimate suggests that high real output growth can lead to future increase in inflation. The $t$-statistics further suggest that all estimates are strongly significant.

We normalize the variance of each innovation to one, but allow the innovation to have contemporaneous correlations. The contemporaneous correlation estimate is negative at $-0.2541$ and statistically significant. Therefore, the nominal and the real side of the economy interact not only predictively, but also contemporaneously. These dynamic interactions dictate that the inflation risk can also enter the real side of the pricing kernel.

Given the parameter estimates, the Kalman filter extracts the economic factors from the 11 observed series. Figure 1.1 plots the time series of the two economic factors. The inflation factor (solid line) shows spikes in late 1974 and early 1980, but is significantly lower in other sample periods.

The real growth factor (dashed line) generally coincides with the business cycle defined by NBER. The factor stayed at high values from 1963 to 1969, then experienced two sharp falls between 1970 and 1975. After that, the factor picked up in the middle of 1975 and remained at high values until the mid 1979. After the recession from 1980 to 1982, the factor experienced another period of prolonged high growth from 1983 to 1989. The real growth slowed down between 1991 and 1992, but stayed high during the next five years. Real growth experienced a steep fall in early 2001 and reached the bottom in second quarter of 2002.

## 1.4. Estimating Economic Risk Exposures for Individual Stocks

The extant literature often directly regresses market portfolio returns on a few economic indicators. In addition to the large noise and instability issue induced by directly using economic indicators as regressors, this practice also largely ignores the fact that changes in the state of economy can impact both the cash flows and the pricing kernel. Without controlling for the cash flow effect, it is inherently difficult to directly link the regression coefficients to the market pricing of economic risks. Furthermore, the results based on a single market portfolio series are prone to lacking statistical power. Since the pricing kernel affects the pricing of not only the market portfolio, but also each single individual stocks, fully exploiting the cross-sectional information in individual stocks not only helps us control the cash flow effect, but also provides us with more statistical power in identifying the risk-return relation. In this section, we exploit the fact that cash flows from different firms often show different correlations with the state of the economy. By regressing returns on each stock on the two economic risk factors, we can identify the different risk exposure for different stocks through the difference in the regression coefficients.

### 1.4.1. Rolling window estimation of risk exposures for individual stocks

To measure the risk exposure for each individual stock, we first define the shocks on the two economic risk factors at time $t$ as the difference between the the ex post filtering updates and their ex ante predictions on the two economic factors: $ES_t = \widehat{X}_t - \overline{X}_t$. Table 2.3 provides the descriptive statistics on the economic shocks. The mean and median levels of the economic shocks are close to zero, indicating that the Kalman filter generates largely unbiased forecasts on the economic factors. The two normalized economic factors have shocks with a range of about $\pm 4$ and standard deviations of around one. The shocks show only modest autocorrelation as compared to the high persistence in the economic factors, indicating that our factor dynamics are reasonably well-specified.

To estimate the risk exposure for each stock $i$, we regress its monthly returns ($r_t^i$, in monthly percentages) on the two economic shocks contemporaneously:

$$r_t^i = \beta_0 + \beta_\pi^i ES_{\pi,t} + \beta_g^i ES_{g,t} + e_t^i, \tag{1.6}$$

where the coefficients $\beta_\pi^i$ and $\beta_g^i$ measure the exposures for stock $i$ to systematic shocks in inflation and real output growth, respectively. Since internal consistency requires that one pricing kernel prices all the stocks, the cross-sectional difference in the coefficient estimates reflects the differences in cash flow effects.

Because economic risk exposures for each company can vary over time, we estimate the regression using a rolling window. Meanwhile, to obtain stable risk exposure estimates, we use a relatively long window of ten years so that the regression sample period cover at least a full business cycle, as in Hoberg and Phillips (2006). We perform the rolling sample estimation once a year starting in January 1963. Thus, for a stock that spans the whole sample from January 1953 to December 2005, we perform the estimation 43 times. The coefficients are maintained constant within each year. For a stock to be included for the risk exposure estimation in a rolling window, we require that the stock has no fewer than 36 months of observation within the rolling window.

### 1.4.2. Cross-sectional and time-series variations in risk exposures

Table 1.5 reports the summary statistics on the risk exposure estimates on inflation (panel A) and the real output growth (panel B). To understand how the risk exposures vary across different stocks, we first average the rolling window estimates on each stock, and then compute the cross-sectional statistics on the time-series averages across different stocks. The statistics are reported in the first column. There are altogether 15,552 stocks in our sample. The mean estimate on the inflation risk exposure is $-0.6014$, very small compared to the standard deviation estimate of 2.8589. The estimates vary greatly across stocks, from as low as $-12.9316$ to as high as 15.7398. Recall that the standard deviation estimate for the inflation shocks is 0.9378 (Table 2.3). Multiplying the standard deviation with the risk exposure coefficients, we observe that each one standard deviation positive shock on the inflation factor can drive down some stock's return by as much as 12.13% per month, while driving up some other stock's return by 14.76% per month.

Similar observation applies to the exposure estimates on the real output growth factor. The cross-sectional mean is $-1.4045$, again small compared to the cross-sectional standard deviation of 4.9265. The real exposure estimates range from $-34.8307$ to 16.8267. Comparing these estimates with the standard deviation of the real output growth shock at 0.9836 (Table 2.3), we observe that a one standard deviation positive shock on the real output growth risk can drive some stocks up by 16.55% per month, while driving some other stocks down by 34.26% per month. These statistics suggest that exploiting the cross-sectional variation is important in identifying the market pricing of economic risks.

To analyze the stability of the risk exposure estimates over time, we first compute cross-sectional averages of the risk exposure estimates at each year and then report the time-series statistics of the cross-sectional averages in the second column. In contrast to the large cross-sectional variation, the time-series variation is much smaller. The time-series standard deviation is 0.8589 for the average inflation exposure estimates and 1.2549 for the real output growth exposure estimates. Both estimates are less than one third of the corresponding cross-sectional standard deviation estimates.

Previous studies often regress market portfolio returns on economic indicators, and use the regression coefficients to capture the linkage between the stock market and the fundamentals. For comparison, we perform a similar exercise by estimating the rolling window regression on the market portfolio returns. The results are reported in the last column in Table 1.5. By using the systematic economic factors instead of using some noisy economic indicators as often done in the literature, our regression should generate more significant coefficient estimates as it suffers less from the error-in-variable and/or multicollinearity problems. Nevertheless, the estimates remain very small compared with the estimates on some individual stocks. The rolling window regression generates 43 coefficients on both inflation and real output growth. The mean and median coefficients on inflation are negative, but the estimates vary over time from $-1.5520$ to 0.7216. Compared to the standard deviation of 0.5541, the mean estimate is statistically significant as often found in the literature, but its modest magnitude dramatically underestimates the strong risk exposures (of either directions) of some stocks to the economic shocks. The mean estimate of $-0.5149$ implies a mere $-0.48\%$ market response per one standard deviation positive shock on the inflation risk factor.

The estimates are even weaker on the real output growth factor. The mean estimate is slightly negative at $-0.2686$, but the median estimate is slightly positive at 0.0426. Neither is statistically significant compared to the standard deviation estimate. The insignificant estimate on the market portfolio again contrasts sharply with the large estimates on some individual stocks. Therefore, focusing on the market portfolio can lead to the erroneous conclusion that real output growth does not matter for stock valuation.

To provide further evidence on our argument that economic risks exert different impacts on different types of firms, we also use the rolling window regression to estimate the economic risk exposures on ten industry portfolios. The portfolio definitions and value-weighted excess returns on the portfolios are available at Kenneth French's online data library. Table 1.6 reports the summary statistics of the risk exposure estimates on each of the ten industry portfolios. The contemporaneous relation between inflation and stock returns is relatively uniform across different industries. High inflation is associated with lower average returns for all ten industries. In contrast, the exposure to the real output growth factor shows larger cross-sectional variations. For example, the consumer durables industry shows positive exposures on average, indicating that the industry is pro-cyclical. On the other hand, the consumer non-durables industry shows strong counter-cyclical behavior as the average risk exposure estimate on the real output growth is negative. Averaging the risk exposure of pro-cyclical companies with that of counter-cyclical companies is likely to generate insignificant estimates.

## 1.5. Estimating Market Prices of Economic Risk Exposures

Given the risk exposure estimates on individual stocks, we can proceed to investigate whether and how the financial market prices the two economic risks. If the market does not price an economic risk, the expected return on each stock will not vary with the sign and magnitude of its exposure to the economic risk. On the other hand, if the market dislikes a source of economic risk, expected returns on stocks with high positive exposures to this economic risk will be higher than on stocks with negative exposures. The higher expected return constitutes a compensation or premium for bearing this risk. Conversely, if the market favors an economic exposure, the market will be willing to accept a lower expected return to bear more of this economic risk.

Based on these arguments, we use two approaches to measure the market pricing of the two economic risks. First, we form stock portfolios based on their risk exposure rankings, and we use the average return differences across these portfolios to measure the average risk premium attributable to the risk exposures. Second, we run cross-sectional regressions in each month that linearly relate the next month's return of each stock to its current exposures in the two economic risks.

### 1.5.1. The portfolio approach

In the first approach, we form stock portfolios based on the risk exposure rankings, and then gauge the difference in average returns across these portfolios. Specifically, we compute the equal-weighted returns on 100 portfolios formed based on their relative exposures to the inflation and real output growth risk. The procedure is similar to those outlined in Fama and French (1992, 1993, 1995, 1996). Starting from 1963 and in December of each year $t$, we first rank all NYSE common stocks based on their exposure estimates to the inflation risk. Then, we break NYSE, AMEX, and Nasdaq stocks into ten inflation exposure groups based on the breakpoints of the NYSE stock deciles. Analogously, we rank all NYSE stocks in CRSP based on their real output growth betas, and we break NYSE, AMEX, and Nasdaq stocks into ten output exposure groups based on the breakpoints of the NYSE stock deciles. Finally, we intersect the 10 groups based on inflation betas with the 10 groups based on output betas to generate 100 portfolios of the NYSE/AMEX/Nasdaq stocks.

The returns on the 100 portfolios have cross-correlations between 0.58 and 0.93, with a sample average of 0.78. If these correlations are in part induced by their common loadings on the economic risk factors, we would expect higher correlations between portfolios with similar economic risk exposures and lower correlations between portfolios with different risk exposures. To test this hypothesis, we regress the correlation estimate between each pair of portfolio on their distance in terms of their rankings in inflation and real output growth betas,

$$\begin{array}{cccccccc} \rho_{ij} & = & 0.8008 & - & 0.0086 D_{\pi}^{ij} & - & 0.0044 D_{g}^{ij} + e, \\ & & (155.40) & & (9.57) & & (5.67) \end{array} \tag{1.7}$$

where $D_{\pi}^{ij}$ denotes the absolute distance in inflation risk exposure ranking between portfolio $i$ and $j$, and $D_{g}^{ij}$ denotes the distance in real output growth ranking. The numbers in parentheses below the estimates are the absolute values of the $t$-statistics. Consistent with our conjecture, the correlation between two portfolios declines as the difference between two portfolios' exposures to the economic risks increase. This result tells us that at least from the cash flow effect perspective, both the nominal and real economic risks affect the stock valuation significantly.

To analyze the pricing effect, we compare the average returns on these portfolios and investigate how the average returns vary with the risk exposures. Table 1.7 reports the average returns on the 100 portfolios ranked by risk exposures to inflation and real output growth risks. The last row reports the average spread between the highest and the lowest real output growth beta portfolios at 0.19% per month with a $t$-value of 1.81, and an average spread between the highest and the lowest inflation beta portfolios at $-0.30\%$ per month, with a $t$-value of 2.39. Moreover, nine out of the ten spreads between the highest and the lowest inflation beta portfolios after controlling for output growth beta are negative, as shown in the last two columns under $\beta_\pi^{10} - \beta_\pi^1$. Nine out of ten spreads between the highest and the lowest output growth beta portfolios after controlling for inflation beta are positive, as shown by the two rows under $\beta_g^{10} - \beta_g^1$. These average return spreads suggest that the stock market charges a positive risk premium on exposures to the real output growth risk and a negative risk premium on exposures to the inflation risk.[3]

These average return spreads suggest that the stock market charges a positive risk premium on positive exposures to the real output growth risk. Thus, pro-cyclical companies are regarded as more risky and demand a higher expected excess return than counter-cyclical companies. The estimates further suggest that investors ask for a negative risk premium on positive exposures to the inflation risk. Table 1.6 shows that most industries have negative exposures to inflation. The more negative the inflation exposure is, the higher the premium investors demand.

### 1.5.2. The cross-sectional regression approach

In the second approach, as in Fama and MacBeth (1973), we run a cross-sectional regression at each month period between the stock returns and the two risk exposure estimates:

$$r_{t+1}^i = \alpha_{0,t} + \alpha_{\pi,t}\beta_{\pi,t}^i + \alpha_{g,t}\beta_{g,t}^i + \varepsilon_t^i, \tag{1.8}$$

[3]For robustness check, we have also experimented with different portfolio partitions, such as 10 by 5 inflation/output portfolios. The results are qualitatively the same.

where $r^i_{t+1}$ denotes the realized return on stock $i$ from month $t$ to $t+1$, $\beta^i_\pi$ and $\beta^i_g$ are the rolling window risk exposure estimates on stock $i$ in month $t$. For robustness control, we truncate the values for the smallest and largest 0.5% of the observations on $\beta_{\pi,t}$ and $\beta_{g,t}$ to the next smallest or largest values. Through this cross-sectional regression, we obtain three coefficient estimates in each month. Then, the time-series averages of the two slope coefficients reflect the risk premium charged for each risk exposure.

Table 1.8 reports the time series averages and $t$-statistics on the slope coefficients of the Fama-MacBeth regressions. We run both univariate regressions on each beta and joint regressions on the two economic risk betas. The results from both types of regressions are similar, and consistent with the average returns from the portfolio spreads. Over the whole sample period from January 1963 to December 2005, the slope coefficient on the inflation beta is negative and statistically significant. The slope coefficient on the real output growth beta is positive and also statistically significant.

Based on the full sample, the joint regression generates an average slope coefficient of $-0.0673$ on the inflation beta and 0.0555 on the output growth beta. As reported in Table 1.5, the cross-sectional standard deviation of the time-series average inflation beta is 2.8589 and that on the real output growth beta is 4.9269. Multiplying the standard deviations with the slope coefficient estimates, we can compute that a one standard deviation variation in the inflation beta leads to an expected return difference of $-0.19\%$ per month, and a one standard deviation variation in the real output growth beta generates an expected return spread of 0.27% per month. These estimates are in line with the average return spreads on the ranked portfolios in Table 1.7.

### 1.5.3. Time varying risk premiums

To analyze how the average risk premiums on the two economic risks vary over time, we also perform subsample analysis on the coefficients. In Table 1.8, the statistics in panel B are for the subsample period from January 1963 to December 1985 and the statistics panel C are for the subsample period from January 1986 to December 2005. Although the signs of the estimates from each subsample period are consistent with that from the full-sample estimates, the magnitudes of the risk premiums do vary across sample periods. In particular, the risk premium estimates on both economic risks are larger in absolute magnitude during the first subsample from 1963 to 1985 than during the second subsample from 1986 to 2005.

The lower risk premium in the second subsample period can be either due to lower market price per unit risk, or lower risk level, or both. To disentangle the two effects, we perform a GARCH estimation on the conditional variance of the two economic risks. Specifically, we assume that the conditional mean of the two economic shock series ($ES$) follow an AR(1) process and that the conditional variance of the economic shocks follow an asymmetric GARCH process (Glosten, Jagannathan, and Runkle (1993)):

$$ES_{t+1} = \alpha_0 + \alpha_1 ES_t + \varepsilon_{t+1}, \tag{1.9}$$

$$\mathbb{E}_t\left[\varepsilon_{t+1}^2\right] \equiv \sigma_t^2 = \gamma_0 + \gamma_1\varepsilon_t^2 + \gamma_2\sigma_t^2 + \gamma_3\varepsilon_t^2 1_{\varepsilon_t<0}, \tag{1.10}$$

where $1_{\varepsilon_t<0}$ is an indicator function that is unity when $\varepsilon_t < 0$ and zero otherwise. The indictor function introduces an asymmetric volatility response to past shocks. Table 1.9 reports in panel A the maximum likelihood estimates on the parameters that govern the dynamics of the two economic shocks series. For inflation shocks, the asymmetric coefficient $\gamma_3$ is negative, indicating that the conditional variance on the inflation shock is higher when inflation is high. On the other hand, the coefficient estimate is positive for the real output growth factor, indicating that the conditional variance on the real output growth is higher in the presence of negative real shocks. The monthly autocorrelation estimates $\alpha_1$ on the two economic shocks are both around 0.3, close to the sample estimates in Table 1.5.

Table 1.9 in panel B reports the sample statistics of the conditional variance estimates on the two economic shocks for both the whole sample period and the two subsample periods. During the whole sample period, the average conditional variance on the inflation shocks is 0.8964, and the average conditional variance on the real output growth shocks is 0.4657. The conditional variance estimates on both economic shocks are highly persistent, with monthly autocorrelations estimate at around 0.95. Comparing the average conditional variances over the two subsamples, we observe lower conditional variance level during the second subsample period than during the first subsample. The sample average of the conditional variance during the first subsample is 0.94 for inflation and 0.68 for the real output growth shocks. The sample averages of the conditional variances are lower during the second subsample, at 0.85 for inflation shocks and 0.22 for real output growth shocks. Thus, the declining risk levels in the economic shocks contribute at least in part to the lower risk premium estimates observed in the second subsample period.

### 1.5.4. Economic interpretations and implications

By extracting two dynamic economic factors from a large array of economic indicators, and by carefully separating the cash flow effect from the pricing kernel effect while exploiting the information content in the large cross section of individual stocks, we find that both real and nominal economic risks are significantly priced by the stock market. Investors dislike positive exposures to real output growth shocks and ask for a positive premium to bear such exposures. However, investors favor positive exposures to inflation risk, and are willing to accept a lower expected return for stocks with high and positive exposures to the inflation risk. Both findings have important implications for asset pricing theory.

The significantly positive market price estimate on the real output growth risk provides much needed empirical support for classic asset pricing theories that advocate consumption smoothing. Under these theories, investors dislike assets with cash flows that are positively correlated with real aggregate consumption growth. Our real output growth factor can be regarded as a proxy for the real aggregate consumption growth.

On the other hand, the significantly negative market price estimate on the inflation risk suggests that inflation can also enter the real side of the pricing kernel. Historically, researchers (e.g., Bodie (1976)) argue that nominal returns on stocks can be used to hedge against inflation risk to gain steadier real consumption flow. This hedging is more effective when the stock's exposure to inflation risk is stronger. This hedging argument can potentially generate a negative market price for the inflation risk. Furthermore, several authors (e.g., Fama (1981) and Piazzesi and Schneider (2006)) also point to the dynamic interactions between real growth and inflation for possible explanations on why inflation enters the real side of the pricing kernel. Our estimated economic factor dynamics also indicate that inflation and real output growth not only show negative contemporaneous correlations, but they also dynamically predict each other. In particular, high inflation predicts future slowing down in real output growth, whereas high real growth can generate high future inflation. As a result, stocks with high positive correlations with the inflation factor can play a hedging role against future real consumption risks. Investors are willing to accept a lower expected return for the hedging benefit.

In an influential paper, Campbell and Vuolteenaho (2004) break the beta of a stock with the market portfolio into two components, one reflecting news about the market's future cash flows and one reflecting news about the market's discount rates. They regard cash flow exposure as "bad beta" that requires a high premium for compensation, but regard positive discount rate exposure as "good beta" that investors are willing to gain exposure for lower expected return. In this paper, we decompose the aggregate economy into two fundamental dimensions: the real output growth and inflation. The two risk dimensions enter both the cash flows and the discount rates. The real output growth shows mainly a cash flow effect. A positive shock on the real output growth predicts positively on future cash flows and hence generates a "bad beta". In some monetary policy rules such as the famous Taylor (1993) rule, a positive shock on the real output growth also partially increases the short-term nominal interest rate, but this influence becomes smaller as the central bank emphasizes more on inflation targeting. On the other hand, a positive shock on inflation predicts negatively on future real cash flow growth. Furthermore, under most scenarios, central banks must raise the short-term nominal interest rate more than the increase in the expected inflation. Through this over-proportionate increase in the nominal rate, the central banks effectively raise the real interest rate as a way to fight against potential overheating of the economy. Therefore, a positive inflation exposure generates both a negative cash flow effect and a positive discount rate effect, both of which generate “good beta” and hence negative risk premium.

## 1.6. Conclusion

Despite the classic asset pricing theories that link financial security returns to economic fundamentals, empirical work often fails to identify a significant relation. We attribute the empirical failure to two major challenges in correctly measuring the linkages. First, a large array of economic indicators are available, all with some information about the systematic state of the economy but also with a large amount of noise. Directly incorporating these economic indicators into regressions often generate unreliable results due to errors-in-variable issues, and potentially multicollinearity issues. Second, economic fundamentals affect stock returns through their impacts on both the company’s cash flows and the market’s pricing kernel. Different types of companies often have cash flows that vary differently with the state of the economy, but stocks on all these companies should be priced by one pricing kernel to maintain internal consistency. Therefore, it is important to control the cash flow effect in order to identify the market pricing of the economic risk exposures.

To resolve the first challenge, we propose a dynamic factor model to summarize the information and suppress the noise in a large array of economic indicators. Based on this approach, we extract two systematic dynamic economic factors from 11 economic series. One captures the nominal side of the economy, which we label as inflation. The other captures the real side of the economy, which we label as real output growth.

Then, to effectively separate the cash flow effect from the pricing kernel effect, we first regress returns on each individual stock on the two systematic economic risks to obtain a risk exposure estimate for each stock. Given the same pricing kernel, the difference in the coefficient estimates reveals the difference in the cash flow dependence on the state of the economy across different stocks. Then, we use three different approaches to measure how the expected stock returns vary with the risk exposures, from which we determine the market pricing of economic risk.

We find that the market charges a positive price on the real output growth risk. This finding provides the much-needed empirical support for classic asset pricing theories that argue for consumption smoothing. Investors dislike stocks with cash flows that are positively correlated with the aggregate output growth, and hence ask for a premium to bear such positive co-movement. On the other hand, we find that the market also charges a negative price on the inflation risk. This finding suggests that inflation risk can also enter the real side of the pricing kernel through its dynamic interactions with the real output growth risk.

Table 1.1

Summary statistics of the macroeconomic series

Entries report the summary statistics of the 11 macroeconomic series (in annualized percentages) that we use to extract two systematic economic factors. They include the mean, median, minimum, maximum, standard deviation (Std. Dev.) and the first-order autocorrelation (Auto) at each series' sampling frequency. For each series, we also report its sampling frequency, its starting date, and the number of observations (Nobs) used for our model estimation.

| Series | Mean | Median | Minimum | Maximum | Std. Dev | Auto | Frequency | Starting Date | Nobs |
|---|---|---|---|---|---|---|---|---|---|
| CPI | 3.875 | 3.157 | -1.111 | 14.592 | 2.956 | 0.992 | M | Jan 1953 | 636 |
| Core CPI | 4.153 | 3.346 | 0.654 | 13.604 | 2.678 | 0.994 | M | Jan 1958 | 576 |
| PPI | 3.180 | 2.509 | -2.823 | 19.492 | 3.745 | 0.983 | M | Jan 1953 | 636 |
| Core PPI | 3.567 | 2.544 | -0.598 | 17.400 | 3.217 | 0.968 | M | Jan 1975 | 372 |
| PCE | 3.784 | 3.086 | 0.502 | 11.477 | 2.511 | 0.994 | M | Jan 1960 | 552 |
| Core PCE | 3.672 | 3.535 | 0.901 | 9.939 | 2.223 | 0.995 | M | Jan 1960 | 552 |
| GDP Deflator | 3.536 | 2.779 | 0.792 | 11.008 | 2.358 | 0.983 | Q | Mar 1953 | 212 |
| Nonfarm Payroll | 1.933 | 2.327 | -4.207 | 5.635 | 2.028 | 0.981 | M | Jan 1953 | 636 |
| Industrial Production | 3.385 | 3.805 | -12.421 | 21.668 | 5.303 | 0.961 | M | Jan 1953 | 636 |
| Real PCE | 3.602 | 3.648 | -2.087 | 8.662 | 1.889 | 0.903 | M | Jan 1960 | 552 |
| Real GDP | 3.334 | 3.605 | -3.047 | 9.470 | 2.478 | 0.833 | Q | Mar 1953 | 212 |

Table 1.2
Extracting systematic dynamic factors from economic indicators
Entries report the estimates and the $t$-statistics (in parentheses) of parameters ($H$) that link each economic indicator series to the systematic dynamic factors. Entries under $R$ report the measurement error variance estimates and $t$-statistics for each series. The last column reports the predicted variation of the factors on each series, defined as one minus the ratio of the forecasting error variance over the variance of the original series. The parameters are estimated with maximum likelihood method joint with Kalman filter using 11 macroeconomic series obtained from the Federal Reserve Board. The sample period is from January 1953 to December 2005.

| Macroeconomic Indicators | Loading coefficients ($H$) on Inflation ($\pi$) | | Loading coefficients ($H$) on Real Growth ($g$) | | Measurement Error variance ($R$) | | Predicted Variation |
|---|---|---|---|---|---|---|---|
| CPI | 0.2737 | ( 27.83 ) | — | ( — ) | 0.4941 | ( 13.63 ) | 0.950 |
| Core CPI | 0.2367 | ( 17.95 ) | — | ( — ) | 0.9266 | ( 13.43 ) | 0.885 |
| PPI | 0.3248 | ( 25.51 ) | — | ( — ) | 2.4137 | ( 14.06 ) | 0.818 |
| Core PPI | 0.2822 | ( 26.71 ) | — | ( — ) | 1.1644 | ( 17.99 ) | 0.900 |
| PCE | 0.2360 | ( 33.11 ) | — | ( — ) | 0.0000 | ( 0.00 ) | 0.991 |
| Core PCE | 0.1983 | ( 21.18 ) | — | ( — ) | 0.4909 | ( 9.60 ) | 0.911 |
| GDP Deflator | 0.2152 | ( 27.26 ) | — | ( — ) | 0.4456 | ( 10.73 ) | 0.939 |
| Nonfarm Payroll | 0.0771 | ( 14.43 ) | 0.3936 | ( 42.82 ) | 0.0000 | ( 0.00 ) | 0.965 |
| Industrial Production | — | ( — ) | 0.8205 | ( 31.22 ) | 7.0455 | ( 16.45 ) | 0.656 |
| Real PCE | — | ( — ) | 0.2489 | ( 19.18 ) | 1.8972 | ( 15.34 ) | 0.402 |
| Real GDP | — | ( — ) | 0.3849 | ( 19.47 ) | 1.5013 | ( 9.16 ) | 0.682 |

Table 1.3
Inflation and real output growth dynamics
Entries report the estimates on the autocorrelation matrix $\Phi$ and the innovation covariance matrix $Q$ of the two economic risk factors. The innovation variance is normalized to one for both factors. The $t$-statistics are reported in parentheses. The dynamics are estimated with maximum likelihood method joint with Kalman filtering using 11 macroeconomic series obtained from the Federal Reserve Board. The sample period is from January 1953 to December 2005.

| | $\Phi$ | | $Q$ | |
|---|---|---|---|---|
| Inflation ($\pi$) | 1.0070 | 0.0568 | 1 | -0.2541 |
| | ( 203.54 ) | ( 5.62 ) | ( — ) | ( -4.67 ) |
| Real Growth ($g$) | -0.0183 | 0.9700 | -0.2541 | 1 |
| | ( -3.59 ) | ( 112.48 ) | ( -4.67 ) | ( — ) |

Table 1.4
Descriptive statistics on the systematic economic shocks
Entries report the descriptive statistics on the systematic economic shocks, defined as the difference between the ex post filtering updates on the economic factors and their ex ante forecasts. The sample period is from January 1953 to December 2005, 576 monthly observation on each series.

| Statistics | Inflation shocks | Output shocks |
|---|---|---|
| Mean | 0.0067 | -0.0255 |
| Median | -0.0233 | -0.0213 |
| Minimum | -3.1702 | -4.4899 |
| Maximum | 3.5845 | 3.5681 |
| Standard Deviation | 0.9378 | 0.9836 |
| Autocorrelation | 0.3093 | 0.4223 |

Table 1.5
Descriptive statistics on economic risk exposure estimates
Entries report the cross-sectional summary statistics of the time-series average risk exposure estimates across different stocks, and the time-series summary statistics of the cross-sectional average risk exposure estimates. The last column reports the statistics on the risk exposure estimates of the market portfolio. The risk exposure estimates are obtained by regressing monthly returns for individual firms on shocks to inflation and real output growth with a ten-year rolling window.

| | Cross-sectional statistics on time-series averages | Time-series statistics on cross-sectional averages | Risk exposure on market portfolio |
|---|---|---|---|
| Panel A: Exposure to inflation risk | | | |
| Mean | -0.6014 | -0.7242 | -0.5149 |
| Median | -0.7703 | -0.8893 | -0.5490 |
| Minimum | -12.9316 | -1.9682 | -1.5520 |
| Maximum | 15.7398 | 1.3289 | 0.7216 |
| Std. Dev. | 2.8589 | 0.8589 | 0.5541 |
| Panel B: Exposure to output risk | | | |
| Mean | -1.4045 | -0.5255 | -0.2686 |
| Median | -0.4085 | -0.0496 | 0.0426 |
| Minimum | -34.8307 | -3.5940 | -2.3046 |
| Maximum | 16.8267 | 1.3192 | 0.6776 |
| Std. Dev. | 4.9265 | 1.2549 | 0.7973 |

Table 1.6

Descriptive statistics on economic risk exposure estimates by industry

Entries report summary statistics on the time-series risk exposure estimates on inflation (Panel A) and output growth (Panel B) for 10 industries.

| Industry | Mean | Median | Minimum | Maximum | Std. Dev. |
|---|---|---|---|---|---|
| Panel A: Exposure to inflation risk | | | | | |
| Consumer NonDurables | -0.7706 | -0.7768 | -1.5654 | 0.2307 | 0.4720 |
| Consumer Durables | -0.5660 | -0.7388 | -1.4056 | 1.1959 | 0.6348 |
| Manufacturing | -0.5034 | -0.6100 | -1.2947 | 0.9529 | 0.5642 |
| Energy Oil, Gas, and Coal Extraction and Products | -0.0775 | -0.1808 | -1.3621 | 1.2032 | 0.6478 |
| HiTec Business Equipment | -0.5302 | -0.5091 | -2.0186 | 1.4814 | 0.8342 |
| Telephone and Television Transmission | -0.6484 | -0.6408 | -1.3986 | 0.1811 | 0.3508 |
| Wholesale, Retail, and Some Services | -0.8515 | -0.7535 | -1.8881 | 0.3737 | 0.6160 |
| Healthcare, Medical Equipment, and Drugs | -0.7693 | -0.9402 | -2.0829 | 0.9799 | 0.6558 |
| Utilities | -0.5405 | -0.5738 | -1.0649 | 0.2974 | 0.3297 |
| Panel B: Exposure to output risk | | | | | |
| Consumer NonDurables | -0.5540 | -0.2715 | -3.2087 | 0.6380 | 0.9231 |
| Consumer Durables | 0.1014 | 0.4198 | -1.7078 | 0.9242 | 0.7079 |
| Manufacturing | -0.1350 | 0.1184 | -2.1663 | 0.8620 | 0.8135 |
| Energy Oil, Gas, and Coal Extraction and Products | -0.0068 | 0.1052 | -1.1664 | 0.6711 | 0.4397 |
| HiTec Business Equipment | -0.3101 | 0.0781 | -3.6804 | 0.7721 | 1.0189 |
| Telephone and Television Transmission | -0.0442 | 0.0624 | -1.1453 | 1.0316 | 0.4894 |
| Wholesale, Retail, and Some Services | -0.5069 | -0.2526 | -2.8141 | 0.8773 | 1.0037 |
| Healthcare, Medical Equipment, and Drugs | -0.7213 | -0.3728 | -3.8756 | 0.7397 | 1.2617 |
| Utilities | -0.0692 | -0.0476 | -1.4573 | 0.9137 | 0.4638 |

Table 1.7

Average returns on portfolios ranked by exposures to inflation and output risks

Entries report the mean returns on 100 portfolios ranked by their exposures to inflation risk ($\beta_\pi$) and real output growth risk ($\beta_g$). A low rank number means low (or negative) exposure and a high rank means high (positive) exposure. The last two columns report the mean return differences and their absolute magnitudes of the $t$-statistics (in parentheses) between the highest inflation exposure portfolios and the lowest inflation exposure ($\beta_\pi^{10} - \beta_\pi^1$) portfolios at each output exposure rank. The two rows under ($\beta_g^{10} - \beta_g^1$) report the mean return differences and their absolute $t$-statistics (in parentheses) between the highest output exposure portfolios and the lowest output exposure portfolios at each inflation exposure rank. The last row reports the average risk premium on the two risk exposures. The sample period is from January 1963 to December 2005.

| $\beta_g \setminus \beta_\pi$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | $\beta_\pi^{10} - \beta_\pi^1$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.04 | 1.06 | 0.97 | 1.08 | 0.99 | 0.76 | 1.11 | 0.75 | 0.78 | 1.03 | -0.01 | (0.36) |
| 2 | 1.04 | 0.93 | 1.00 | 0.83 | 0.92 | 1.04 | 0.64 | 0.81 | 0.91 | 0.74 | -0.30 | (1.65) |
| 3 | 1.33 | 0.92 | 1.08 | 0.79 | 0.86 | 0.79 | 0.83 | 0.69 | 0.91 | 0.70 | -0.63 | (2.83) |
| 4 | 1.32 | 1.09 | 1.08 | 0.84 | 0.85 | 0.63 | 0.89 | 0.75 | 0.69 | 0.88 | -0.43 | (1.93) |
| 5 | 1.26 | 1.08 | 1.02 | 0.99 | 0.93 | 0.92 | 0.77 | 0.76 | 0.72 | 0.91 | -0.35 | (1.64) |
| 6 | 1.19 | 1.16 | 0.98 | 0.94 | 0.97 | 0.83 | 0.69 | 0.67 | 0.71 | 0.80 | -0.38 | (1.91) |
| 7 | 1.27 | 1.01 | 0.92 | 0.84 | 0.76 | 0.84 | 1.09 | 0.84 | 0.83 | 0.75 | -0.52 | (2.50) |
| 8 | 1.03 | 1.06 | 1.12 | 0.99 | 1.03 | 0.91 | 0.71 | 0.90 | 1.09 | 1.03 | 0.00 | (0.31) |
| 9 | 1.07 | 1.19 | 0.91 | 0.91 | 1.04 | 0.72 | 0.95 | 0.89 | 1.03 | 0.82 | -0.25 | (1.38) |
| 10 | 1.25 | 1.04 | 1.09 | 1.26 | 1.23 | 1.06 | 1.25 | 1.04 | 1.06 | 1.14 | -0.11 | (1.03) |
| $\beta_g^{10} - \beta_g^1$ | 0.21 | -0.01 | 0.12 | 0.18 | 0.23 | 0.30 | 0.15 | 0.29 | 0.29 | 0.11 | | |
| | (1.66) | (0.13) | (1.01) | (1.57) | (1.68) | (1.71) | (1.43) | (1.65) | (1.73) | (0.86) | | |
| Mean output risk premium ($\overline{\beta_g^{10} - \beta_g^1}$) | | | | 0.19 | (1.81) | | Mean inflation risk premium ($\overline{\beta_\pi^{10} - \beta_\pi^1}$) | | | | -0.30 | (2.39) |

Table 1.8
Risk premium estimates from Fama-MacBeth regressions
Entries report the average slope estimates and the $t$-statistics from the Fama-MacBeth regressions for both the full sample and two subsamples.

| Sample period | Inflation risk premium ($\alpha_\pi$) | | Output risk premium ($\alpha_g$) | |
|---|---|---|---|---|
| 01/1963 - 12/2005 | -0.0546 | (2.29) | — | — |
| 01/1963 - 12/2005 | — | — | 0.0397 | (2.18) |
| 01/1963 - 12/2005 | -0.0673 | (2.64) | 0.0555 | (2.84) |
| 01/1963 - 12/1985 | -0.0892 | (2.16) | — | — |
| 01/1963 - 12/1985 | — | — | 0.0682 | (2.35) |
| 01/1963 - 12/1985 | -0.1106 | (2.48) | 0.0934 | (2.83) |
| 01/1986 - 12/2005 | -0.0148 | (0.96) | — | — |
| 01/1986 - 12/2005 | — | — | 0.0069 | (0.04) |
| 01/1986 - 12/2005 | -0.0174 | (1.04) | 0.0120 | (0.59) |

Table 1.9
GRACH dynamics on economic shocks and portfolio returns
Entries report the GARCH dynamics estimates and $t$-statistics (in parentheses) on the two economic risk factors in panel A and the summary statistics of the conditional variance estimates in panel B. The dynamics on each economic shock series is specified as:

$$\begin{aligned} ES_{t+1} &= \alpha_0 + \alpha_1 ES_t + \varepsilon_{t+1}, \\ \mathbb{E}_t\left[\varepsilon_{t+1}^2\right] \equiv \sigma_t^2 &= \gamma_0 + \gamma_1 \varepsilon_t^2 + \gamma_2 \sigma_t^2 + \gamma_3 \varepsilon_t^2 1_{\varepsilon_t < 0}, \end{aligned}$$

Data are monthly from January 1963 to December 2005.

| Panel A: Parameter estimates | | | | | | |
|---|---|---|---|---|---|---|
| | $\alpha_0$ | $\alpha_1$ | $\gamma_0$ | $\gamma_1$ | $\gamma_2$ | $\gamma_3$ |
| Inflation | -0.0192 | 0.3004 | 0.0310 | 0.1176 | 0.8849 | -0.0716 |
| | ( 0.50 ) | ( 6.90 ) | ( 1.98 ) | ( 3.52 ) | ( 24.56 ) | ( 1.96 ) |
| Output | -0.0382 | 0.3189 | 0.0095 | 0.1019 | 0.8657 | 0.0362 |
| | ( 1.51 ) | ( 7.09 ) | ( 2.15 ) | ( 3.93 ) | ( 35.67 ) | ( 1.06 ) |

| Panel B: Summary statistics | | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Median | Minimum | Maximum | Std. Dev. | Auto |
| Full sample: January 1963 - December 2005 | | | | | | |
| Inflation | 0.8964 | 0.7404 | 0.4053 | 3.3248 | 0.4973 | 0.9463 |
| Output | 0.4657 | 0.3636 | 0.1173 | 2.3472 | 0.3443 | 0.9448 |
| Subsample: January 1963 - December 1985 | | | | | | |
| Inflation | 0.94 | 0.746 | 0.4053 | 3.3248 | 0.573 | 0.9616 |
| Output | 0.6783 | 0.5872 | 0.2079 | 2.3472 | 0.3486 | 0.9008 |
| Subsample: January 1986 - December 2005 | | | | | | |
| Inflation | 0.8467 | 0.721 | 0.4242 | 2.4853 | 0.3888 | 0.9013 |
| Output | 0.2232 | 0.2077 | 0.1173 | 0.4858 | 0.0696 | 0.8836 |

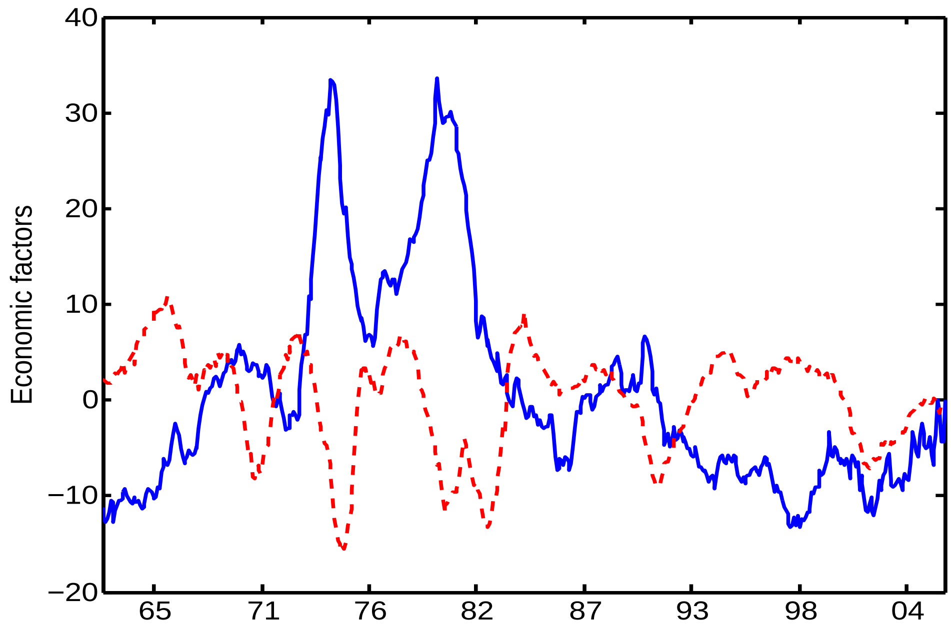


Fig. 1.1. **The time series of the dynamic economic factors.** The solid line plots the time series of the extracted inflator factor. The dashed line is the time series of the extracted real output growth factor.

# Part II

# The Intertemporal Relation between Macroeconomic Risks and Stock Returns

## 2.1. Introduction

In a multiperiod economy, investors have an incentive to hedge against future stochastic shifts in the consumption and investment opportunity set (see Fama (1970)). This implies that state variables that are correlated with changes in consumption and investment opportunities are priced in capital markets in the sense that an asset's covariance with those state variables affects its expected returns (see Merton (1973)).

In his seminal paper, Merton (1973) indicates that any variables that affect the future investment opportunity could be a priced risk factor in equilibrium. Ross (1976) further documents that securities affected by such systematic risk factors should earn risk premia in a risk-averse economy. Macroeconomic variables are excellent candidates for these systematic risk factors, because macroeconomic innovations can generate global impact on firms' fundamentals, such as their cash flows, risk-adjusted discount factors and/or investment opportunities.

Although financial theory suggests that asset prices are influenced by economic news, the theory has been silent about which variables are likely to influence all assets. The empirical work that has tried to establish the risk-return relation between macro changes and security returns is inconclusive. Indeed, the following assessment of the asset pricing literature seems as pertinent today as it was in 1986. Chen, Roll, and Ross (1986) wrote: "*A rather embarrassing gap between the theoretically exclusive importance of systematic "state variables" and our complete ignorance of their identity. The comovements of asset prices suggest the presence of underlying exogenous influences, but we have not yet* *determined which economic variables, if any, are responsible.*"

The stock price movements as reactions to changes in economic indicators have been investigated by a number of studies which often hypothesize that stock prices fell because of disappointing unemployment figures or rose because of encouraging news on the inflation front. There has been, however, little systematic evidence on the quantitative impact on stock prices of such economic news. One obstacle to research in this area is the difficulty in distinguishing that part of an announcement which was unanticipated. According to the efficient markets hypothesis, security prices should only respond to the unexpected part of any announcement - that part of which is truly news - since the expected part of the announcement should already be embedded in stock prices. This paper uses a maximum likelihood estimation joint with Kalman filter to generate innovations in inflation and real economic activity and then examines the response of stock prices to unexpected changes in these macroeconomic variables.

Based on the intertemporal capital asset pricing model (ICAPM) of Merton (1973), we test whether innovations in macroeconomic variables are risks that are rewarded in the stock market. We first estimate the conditional covariances between excess returns on a large cross section of stock portfolios and the economic shocks using a bivariate GARCH model and then test whether the portfolios' conditional covariances with macroeconomic innovations affect the portfolios' expected returns.

The basic approach taken in previous empirical work has been to estimate time-series regression of the (excess) aggregate equity returns on a group of macroeconomic variables that proxy for inflation and/or real economic activity. This approach has a number of problems. First, it is difficult to find measures of one state of economy that are unrelated to the other state. Therefore, special caution is needed in interpreting the coefficient estimates and their statistical significance. Second, the errors-in-variables problem is almost inevitable given the fact that the observed variables are an imperfect representation of the state of economy that they are supposed to measure. The errors-in-variables problem is particularly important if the errors are correlated with the explained variable. Third, measurement errors in the proxy variables may be correlated with measurement errors in the dependent variables, creating spurious correlations.

To resolve these statistical problems in an efficient way, we use a dynamic factor model to succinctly summarize the information and suppress the noise in many observed macroeconomic series. We decompose the aggregate economy into two dimensions - inflation and real activity, extracted from 11 macroeconomic series using the maximum likelihood method joint with Kalman filter. We define the economic shocks as the difference between the ex post filtering updates on the states of economy and their ex ante expectations.

It is important to note that Merton (1973) and Ross (1976)'s prediction on the risk-return relation between security return and the systematic risk factors is applicable not only to the aggregate equity return, but also to returns on any individual stocks or portfolios. For the model to be internally consistent, the relation between the expected excess return and the systematic risk factors should be the same across all individual stocks and portfolios. In this paper, we exploit this cross-sectional consistency condition and estimate the common relation across a wide variety of stock portfolios formed based on market beta, size, and book-to-market characteristics. Our expansion to multiple stock portfolios alleviates the problem of low statistical power caused by focusing narrowly on the risk-return relation of a single market return series.

Rather than regressing equity return directly on the economic shocks, we first estimate the conditional covariance between excess returns on a large cross section of stock portfolios and the shocks to inflation and real economic activity, and then estimate the system of equations with a common slope coefficient between excess returns and their conditional covariance. By doing so, we relax the assumption, often implicitly or explicitly imposed in the literature, that the covariance between security returns and the economic shocks is a linear function of the economic shocks.

The parameter estimates from the univariate and bivariate system of equations indicate that the common slope coefficient on the conditional covariance between the excess portfolio returns and innovations in the nominal (real) side of the economy is negative (positive) and statistically significant. In other words, equity returns are negatively related to their conditional covariance with inflation-related shocks and positively related to their conditional covariance with output-related shocks. These results are robust to different portfolio formations, alternative specifications of the conditional covariance, and different distributional assumptions for innovations in returns and macroeconomic variables.

The positive coefficient estimate on the covariance of returns with output-related shocks indicates that an increase in a portfolio's covariance with unexpected economic growth predicts a higher excess return on the portfolio. In the context of Merton (1973)'s ICAPM, this positive slope estimate suggests that an increase in economic growth predicts an increase in optimal consumption and hence a favorable shift in the investment opportunity set. Therefore, a positive correlation of a portfolio's return with economic growth (state variable that moves positively with optimal consumption) reduces intertemporal hedging demand for the portfolio. Intertemporally, an increase in the covariance of returns with unexpected growth leads to a decrease in the hedging demand, which in equilibrium increases the excess return on the portfolio, and hence a positive slope estimate for the conditional covariance of returns with innovations in real activity.

The negative coefficient estimate on the covariance of returns with inflation-related shocks implies that an increase in a portfolio's covariance with unexpected inflation predicts a lower excess return on the portfolio. In Merton (1973)'s original setup, this negative slope estimate suggests that an increase in inflation predicts a decrease in optimal consumption and hence an unfavorable shift in the investment opportunity set. Intertemporally, an increase in the covariance of returns with unexpected inflation leads to an increase in the hedging demand, which in equilibrium reduces the excess return on the portfolio, and hence a negative slope estimate for the conditional covariance of returns with unexpected inflation.

The rest of the paper is organized as follows. Section 2.2 provides a brief literature review. Section 2.3 describes the data, methodology and results from extracting the two dynamic economic shocks. Section 2.4 discusses the data, methodology, and results from estimating the conditional covariances between excess portfolio returns and economic shocks. Section 2.5 examines the risk-return relation between excess portfolio returns and their conditional covariance with the economic shocks. Section 2.6 provides a battery of robustness checks. Section 2.7 concludes the paper.

## 2.2. Literature Review

The empirical evidence on the risk-return relation between macroeconomic factors and equity returns is inconclusive.

Bodie (1976), Fama (1981), Geske and Roll (1983), Pearce and Roley (1983, 1985) document a negative impact of inflation and money growth on equity values. Chan, Chen, and Hsieh (1985), Chen, Roll, and Ross (1986) (hereafter CCR), and Chen (1991) find that changes in aggregate production, inflation, the short-term interest rates, term spread, and default spread are important economic indicators in determining equilibrium expected returns on securities. In time-series analyses, Fama and Schwert (1977), Rozeff (1984), Keim and Stambaugh (1986), Campbell (1987), Campbell and Shiller (1988), and Fama and French (1988, 1989) find that short-term interest rates, expected inflation, dividend yields, term spread, default spread, and lagged stock returns can predict the expected returns of bonds and stocks. These macroeconomic variables are used in the conditional CAPM framework by Harvey (1989, 2001), and Ferson and Harvey (1991, 1999).

CCR find that the default and term spreads are priced risk factors, and that weaker evidence supports inflation a priced risk factor. Shanken and Weinstein (1990) show that CCR's main conclusion depends on the specific method used to form test portfolios. Correcting some of CCR's standard error of estimates for errors-in-variables further reduces the statistical importance of macro factors for equity returns. Lamont (2001) seeks to identify priced macro factors by determining whether a portfolio constructed to "track" the future path of a macro series earns positive abnormal returns. He concludes that portfolios that track the growth rates of Industrial Production, Consumption, and Labor Income earn abnormal positive returns, while the portfolio that tracks the *CPI* does not. Cutler, Poterba, and Summers (1989) (hereafter CPS) find that Industrial Production growth is significantly positively correlated with real stock returns over the period 1926-1986, but not in the 1946-1985 subperiod, which substantially overlaps CRR's 1958-1984 sample period. CPS provide no support for the hypotheses that inflation, money supply, and long-term interest rates reliably affect stock returns. More generally, CPS seek economic news that might explain large stock market returns ex post. Like Roll (1988), they can account for only a very small proportion of total market variability, even using events that were observed after the stock market had reacted. Flannery and Protopapadakis (2002) (hereafter FP) estimate a GARCH model of daily market returns, where realized returns and their conditional volatility depend on 17 macro series' announcements. FP identify six candidates for priced factors: three nominal (CPI, PPI, and a Monetary Aggregate) and three real (Balance of Trade, Employment Report, and Housing Starts). Popular measures of overall economic activity, such as Industrial Production or GNP are not represented.

Grant and Roley (1993) attribute the failure to identify significant macro factors to a shortcoming of the constant-coefficient models being estimated. They suggest that a given announcement surprise may have different implications at different points in the business cycle. For example, an increase in employment might be a bullish sign as the economy emerges from recession, but a bearish sign near a cyclical peak. They estimate a model in which each series' effect depends on overall economic conditions, defined according to the monthly rate of Industrial Production. They find that only two of their eight announcement series significantly affect the S&P 500 portfolio in a constant-coefficient model, but six carry significant coefficients in at least one of the economic regimes. Boyd, Hu, and Jagannathan (2002) also find that macro news has distinctly time-varying effects on equity returns. They examine the impact of unemployment announcement surprises on the S&P 500 return over the period 1948-1995, and conclude that surprisingly high unemployment raises stock prices during an economic expansion but lowers stock value during a contraction. They hypothesize that higher unemployment predicts both lower interest rates and lower corporate profits, and conclude that the relative importance of these two effects vary over the business cycle.

## 2.3. Extracting Dynamic States of Economy and Macroeconomic Shocks

The basic approach taken in previous empirical work has been to estimate time-series regression of the aggregate equity returns on a group of macro variables that proxy for inflation and/or real economic activity. As discussed earlier, this approach has a number of problems: correlation between different states of the economy, errors-in-variables problem, and spurious correlation between dependent and independent variables used in regressions. To address these empirical challenges in an efficient way, we use a dynamic factor model to succinctly summarize the information and suppress the noise in many observed macro series.

### 2.3.1. Important dimensions of the aggregate economy

In applying a dynamic factor model, we first need to specify the dimensions of the factor space. Based on both empirical evidence and economic rationale, we decompose the aggregate economy into two broad dimensions: (1) the nominal side of the economy, and (2) the real side of the economy.

Macroeconomists often decompose the economy into the nominal and real sides and argue that shocks to the two sides of the economy should be separated and treated differently. For example, Woodford (2003) argues from the perspective of monetary policy that nominal shocks should be minimized whereas real shocks should not be intervened.

Early studies by Sargent and Sims (1977), Sargent (1989) and Stock and Waston (1989) also suggest that a nominal and real factor can account for much of the observed variation in major economic aggregates.

### 2.3.2. Estimating dynamic factor models with maximum likelihood and Kalman filter

We describe the economy by fixing a filtered probability space $\{\Omega, \mathcal{F}, \mathbb{P}, (\mathcal{F}_t)_{0\leq t\leq \mathcal{T}}\}$, with some fixed long horizon $\mathcal{T}$. We use $X \in \mathbb{R}^n$ to denote an $n$-dimensional vector Markov process that represents the systematic states of economy. As discussed above, we set $n = 2$. We further assume that the state vector $X$ follows simple VAR(1) dynamics. Under continuous-time notation, $X$ follows a multivariate Ornstein-Uhlenbeck process under the statistical measure $\mathbb{P}$,

$$dX_t \quad = \quad -\kappa X_t dt + dW_t, \tag{2.1}$$

where $W_t$ denotes an $n$-dimensional standard Brownian motion and $\kappa$ controls the mean-reversion speed of the states. For identification purpose, we normalize the long-run mean of the states $X$ to zero and the instantaneous covariance matrix to be an identity matrix. We also constrain $\kappa$ to be a lower triangular matrix.

Next, let $y \in \mathbb{R}^n$ denote a set of macroeconomic time series. The dimension $N$ can be very large, and much larger than the dimension of the state of the economy, $N \gg n$.

In this paper, we choose $N = 11$, which includes seven inflation-related and four output-related series. We summarize the systematic movements underlying the 11 macroeconomic series using two dynamic economic factors via the following linear factor structure,

$$y_t = HX_t + e_t, \tag{2.2}$$

where $H$ is an $(N \times n)$ matrix of factor loading coefficients and $e_t$ denotes an $(N \times 1)$ vector of measurement errors of the data series. We use $\mathcal{R}^y = \mathbb{E}[e_t e_t]^T$ to denote the covariance matrix of the measurement errors. We assume that the measurement errors are independent of the state vector. In our estimation, we further assume that the measurement errors are mutually independent, but with distinct variance: $\mathcal{R}^y_{ii} = \sigma_i^2, i = 1, ..., N,$ and $\mathcal{R}^y_{ij} = 0,$ for $i \neq j$.

If we know the parameters that govern the factor dynamics ($\kappa$), the factor loadings ($H$), and the measurement errors variance ($\mathcal{R}^y$), we can infer the systematic states of the economy from the observed data series, with the technique of Kalman filtering. For this purpose, we rewrite the economic factor dynamics in its discrete-time analog,

$$X_t = \Phi X_{t-1} + \sqrt{Q}\varepsilon_t, \tag{2.3}$$

where $\Phi = \exp(-\kappa\Delta t)$, $Q = I\Delta t$, $\varepsilon_t$ denotes an $(n \times 1)$ iid standard normal random vector, $\Delta t$ denotes the discrete time interval, and $I$ denotes an identity matrix of the relevant dimension. With monthly time interval, we set $\Delta t = 1/12$.

For Kalman filtering, we regard equation (2.3) as our state-propagation equation and equation (2.2) as our measurement equation. Let $\overline{X}_t$, $\overline{V}_t$, $\bar{y}_t$ and $\overline{A}_t$ denote the time $t-1$ ex ante forecast of time $t$ values of the systematic factors, the covariance matrix of the economic factors, the measurement series, and the covariance matrix of the measurement series. Let $\hat{X}_t$ and $\hat{V}_t$ denote the ex post update or filtering on the economic factors and their covariance at time $t$ based on observations $(y_t)$ at time $t$. The Kalman filter provides the efficient updates on these quantities. Specifically, we have the ex ante predictions as

$$\overline{X}_t = \Phi\widehat{X}_{t-1}, \tag{2.4}$$

$$\overline{V}_t = \Phi\widehat{V}_{t-1}\Phi^\top + Q, \tag{2.5}$$

$$\bar{y}_t = H\overline{X}_t, \tag{2.6}$$

$$\overline{A}_t = H\overline{V}_t H^\top + \mathcal{R}^y. \tag{2.7}$$

The ex post filtering updates are

$$\widehat{X}_{t+1} = \overline{X}_{t+1} + K_{t+1}(y_{t+1} - \bar{y}_{t+1}), \tag{2.8}$$

$$\widehat{V}_{t+1} = \overline{V}_{t+1} - K_{t+1}\overline{A}_{t+1}K_{t+1}^\top, \tag{2.9}$$

where $K_{t+1} = \overline{V}_{t+1}H^\top(\overline{A}_{t+1}{}^{-1})$ is the Kalman gain.

We define the macroeconomic shocks as

$$\widehat{X}_{t+1} - \overline{X}_{t+1} \tag{2.10}$$

Thus, we can obtain a time series of the ex ante forecasts and ex post updates on both the mean and covariance of the economic factors and the data series, via the iterative procedure defined by equations (2.4) to (2.9). We use the maximum likelihood method to estimate the model parameters $\Theta \equiv [\kappa, H, \mathcal{R}^y]$ that govern the factor dynamics by assuming that the forecasting errors on the observed time series are normally distributed. We can write the log-likelihood function as

$$\mathcal{L}(\Theta) \quad = \quad -\frac{1}{2}\sum_{t=1}^{N}\left[\log|\overline{A}_{t+1}| - \frac{1}{2}\left((y_{t+1}-\overline{y}_{t+1})^{\top}(\overline{A}_{t+1}{}^{-1})(y_{t+1}-\overline{y}_{t+1})\right)\right] \quad (2.11)$$

where $N$ denotes the number of observations for each series.

### 2.3.3. Data description

Our estimation is based on 11 monthly or quarterly macroeconomic series spanning the period January 1963 to December 2005. The 11 macroeconomic series are from the Federal Reserve Board. They include seven inflation-related series: the consumer price index (CPI), the core CPI, the producer price index (PPI), the core PPI, the personal consumption expenditure (PCE) deflator, the core PCE deflator, and the gross domestic production (GDP) deflator. The GDP deflator is available in quarterly frequency. All other variables are available in monthly frequency. We first convert the price indexes into year-over-year percentage changes, and then standardize each series by subtracting the sample mean and dividing the series by the sample standard deviation.

The CPI measures the average change in the prices of a basket of goods and services bought by a typical urban household. The PPI measures the change in the selling prices received by domestic producers for all finished goods. The PCE deflator measures the average change in the prices of a basket of goods and services purchased by the typical consumer such as individuals and non-profit organizations. Their respective core measures exclude food and energy, the prices of which tend to be highly volatile. The GDP deflator measures the average change in the prices of all goods and services produced by the domestic economy.

Among the seven inflation measures, the CPI is the most cited inflation measures, but the price changes at the wholesale level, as captured by the PPI numbers, are often passed through to the consumer price index in a later date. Hence, tracking prices from the PPI numbers, investors can anticipate inflationary consequences in the coming months. On the other hand, the PCE deflator is becoming the most watched price index from the standpoint of monetary policy and is considered as a "more reliable measure of inflation by the Federal Reserve"[4] for two reasons. First, while the CPI is only representative of the price paid by urban customers, the PCE deflator is a broader measure that covers both urban and rural customers. Second, the PCE deflator is a chain-weighted index that captures shifting spending patterns. In contrast, the CPI is a fixed-weight index that relies on spending patterns several years ago. Each of the above three indices has a corresponding core measure that excludes food and energy. Many economists and investors prefer the core measures because they think that shocks to energy prices are often transitory. Others

[4]Quotes are from the testimony of Alan Greenspan before the Committee on Financial Services, U.S. House of Representatives, July 18, 2001.

disagree. Finally, since the GDP deflator includes all goods and services produced by the domestic economy, it is the most comprehensive measure of inflation. However, the GDP deflator is released quarterly while all other inflation measures are released monthly. In our application, we do not take a stand on which of the seven series provides the most accurate and timely measure of the inflationary pressure. Instead, we include all of them into our estimation and extract one common factor that captures the systematic movements in inflation pressure.

The data set also includes four output and employment series: the real GDP, industrial production, non-farm payrolls, and the real PCE. The real GDP is available in quarterly frequency. The other three series are available in monthly frequency, but the data on real PCE start at a later date in January 1991. The real GDP growth is the broadest measure of the output growth of the domestic economy. Industrial production measures the production of goods. Although it is less comprehensive, it is more timely since the industrial production numbers are released monthly whereas the GDP numbers are released quarterly. Non-farm payrolls measure the number of employees on firm's payrolls. Farms are excluded because of their seasonal nature, which can skew total employment figures. This number is a key indicator of the employment scenario of the economy, which has far-reaching implications for both inflation and output growth. On the demand side of the economy, we include real personal consumption expenditure, which often indicates changes in the state of the economy prior to changes in production. Again, we first turn the four series into year-over-year growth rates and then standardize them before we extract the real growth factor.

In principle, factors can rotate and the loadings can change accordingly without impacting the final result. However, such rotations make it difficult to interpret the economic meanings of the dynamic factors. To improve identification and enhance the economic interpretation of the factors, we put structural constraints on the factor loading matrix. Specifically, we constrain the first factor to have positive loadings on the seven inflation series and the non-farm payroll series and zero loadings on all other series. As such, this first dynamic factor summarizes the inflation pressure in the economy. We constrain the second factor to have nonzero loadings only on real GDP, industrial production and non-farm payroll, and the real component of the personal consumption expenditure. Thus it summarizes the real part of the macroeconomy, which we label as a real output factor.

We estimate the dynamic factors in monthly frequency. For data series that are only available in quarterly frequency or at a later date, we fill the series with missing values. Our estimation method readily accommodates missing data. At each month, we update the dynamic factors based on the available subset of the data.

### 2.3.4. The time-series dynamics of the states of economy and macroeconomic shocks

Table 2.1 report the estimates and the absolute values of the $t$-statistics (in parentheses) of parameters ($H$) that link each observed data series to the two systematic dynamic factors. Entries under ($H_i$) denote the loadings of each series on the $i$th factor. Entries under $\mathcal{R}^y$

report the measurement error variance estimates and $t$-statistics for each series. The last column ($R^2$) reports the predicted variation of the factors on each series, defined as one minus the ratio of the forecasting error variance over the variance of the original series. Since each series is standardized to have a unit unconditional variance, the measurement error variance reflects the relative goodness of fit for each macroeconomic series. The smaller the measurement error variance is, the higher percentage variation the two dynamic factors can explain. Similarly, $R^2$ measures the predictive performance of the two dynamic factors on each of the 11 series. It also reflects the relative informativeness of 11 series in terms of their affinity to the extracted economic factors.

Among the seven inflation variables, the smallest measurement error variance and the highest predicted variation both come from PCE deflator, consistent with the Federal Reserve's emphasis on this measure as a more reliable gauge of the inflation pressure. On the other hand, the largest error variance and the lowest predicted variation both come from PPI, showing that this series is the most noisy or least informative about the inflation pressure. Nevertheless, the loading estimates on all seven series are statistically significant and positive, suggesting that all seven measures contain useful information about the state of inflation. Hence, it is appropriate to use them all instead of picking one against the other.

The non-farm payroll number is a key indicator of the employment scenario of the economy. It has far-reaching implications for both inflation and output growth. Hence, we also allow the first factor to have a nonzero loading on the non-farm payroll series. The loading estimates are smaller than those on the seven inflation variables, but the high $t$-

statistics suggest that this loading estimate is strongly significant and that non-farm payrolls are indeed informative about the inflation pressure of the economy.

Among the four output and employment series, non-farm payrolls also have the highest loading and highest $t$-statistics on the second factor. Furthermore, the measurement error variance estimate on non-farm payroll is neither visually nor statistically different from zero and the predicted variation is highest among all 11 macroeconomic series, showing that the non-farm payrolls series is the most informative about the economy. Again, however, all four series have significantly positive loadings on the second factor. Hence, they are all informative about the real side of economy.

Table 2.2 reports the parameter estimates for $\kappa$, which control the dynamics of the two macroeconomic and financial factors. For identification, we assume a lower triangular structure for the $\kappa$ matrix. Thus the ranking of the two factors determines their dependence structure. We let inflation be the first factor. Thus the prediction of this factor only depends on its own past value. The estimate of 0.067 corresponds to a monthly autocorrelation of 0.994, showing the high persistence of inflation. The second factor is real output, the conditional mean of which depends on lagged values of both the inflation factor and the output factor itself. The estimate of 0.296 corresponds to a monthly autocorrelation of 0.976, lower than that for the inflation factor. The off-diagonal term 0.269 indicates negative cross-correlation between the two macroeconomic factors.

Given the parameter estimates, the Kalman filter generates the ex post updated values of the two dynamic factors from the 11 observed series. Figure 2.1 plots the time series dynamics of the two extracted economic factors and inferred economic shocks. In the upper panel, the solid line denotes the time series of the extracted inflation factor and the dashed line denotes the time series of the extracted real output growth factor.

The inflation factor had a hike in late 1974 and early 1980. The real output growth factor generally coincides with the business cycle defined by NBER. The factor remained at high values from 1963 to 1969. The factor then experienced two sharp falls between 1970 and 1975. After that, the factor picked up in the middle of 1975 and remained at high values until the mid 1979. From 1980 to 1982, the factor remained at low values. From 1983 to 1989, the factor experienced another prolonged high level. Then the factor slowed down between 1991 and 1992. From 1994 to late 2000, the output growth factor remained at high values with some fluctuation. The factor started another very steep fall in early 2001 and reached the bottom in second quarter of 2002. The output growth has picked up since then. This upswing is still continuing as of now, and the current level of this factor is still way below its level reached in 2000.

We define the macroeconomic shocks as the difference between the ex post filtering updates on the states of economy and their ex ante expectations.[5] In the lower panel of Figure 2.1, the solid line denotes the time series of the inflation-related shock and the dashed line denotes the time series of the output-related shock.

Table 2.3 provides the descriptive statistics on the macroeconomic shocks. The $t$-statistics (in parentheses) on the unconditional mean of the statistical macroeconomic

[5]We also used the first-order difference of the economic shocks to proxy for innovations in the aggregate economy. Our results are almost exactly the same. We attribute these results to the high first-order autocorrelation of the dynamic economic factors.

shocks can not reject the null hypothesis that the mean shock equals zero, indicating that the ex ante expectations on the states of economy were unbiased over the full sample period. The innovations in inflation and real activity are negatively correlated over the sample period, with a correlation coefficient of -0.23.

## 2.4. Estimating Conditional Covariance

Merton (1973)'s ICAPM implies the following equilibrium relation between risk and return,

$$\mu = A\Sigma + \Omega B, \tag{2.12}$$

where $\mu \in \mathbb{R}^n$ denotes the expected excess return on a vector of $n$ risky assets, $A$ reflects the average relative risk aversion of market investors, $\Sigma \in \mathbb{R}^n$ denotes the covariance of the excess returns with the market portfolio, $B \in \mathbb{R}^k$ measures the market's aggregate reaction to shifts in a $k$-dimensional state vector that governs the stochastic investment opportunity, and $\Omega \in \mathbb{R}^{n\times k}$ measures the covariance between excess returns on the $n$ risky assets and the $k$ state variables. For any risky asset or portfolio $i$, the relation becomes,

$$\mu_i - r = A\sigma_{im} + \omega_{ix} B, \tag{2.13}$$

where $\sigma_{im}$ denotes the covariance between the returns on the risky asset $i$ and the market portfolio $m$, and $\omega_{ix}$ denotes a $(1 \times k)$ row of covariances between the return on risky asset $i$ and the $k$ state variables $x$.

Equation (2.13) states that in equilibrium, investors are compensated in terms of expected return, for bearing market (systematic) risk, and for bearing the risk of unfavorable shifts in the investment opportunity set.

The literature on the relation between excess market returns ($\mu_m - r$) and macroeconomic variables $x$ often implicitly or explicitly projects the covariance vector $\omega_{ix}$ linearly to the state variables $x$ to obtain the following relation,

$$\mu_m - r = C + \gamma x. \tag{2.14}$$

We examine the risk-return relation between excess equity returns and shocks to macroeconomic fundamentals, which leads us to focus on the hedging demand component of equation (2.13). This focus yields the following risk-return relation,

$$\mu_i - r = C_i + \omega_{ix} B. \tag{2.15}$$

Our work in this article differs from the above literature in two major ways. First, we estimate the risk-return relation (2.15) not on the single series of the market portfolio, but simultaneously on many stock portfolios, and constrain all these portfolios to have the same cross-sectionally consistent proportionality coefficients $B$. Second, we estimate the time-varying conditional covariances $\omega_{ix}$, and we do not make any linear projection assumptions on the state variables.

In Merton (1973)'s original setup, the covariance $\Omega$ in equation (2.12) is assumed to be constant. Nevertheless, the empirical literature has estimated the relation assuming time-varying covariance. We do the same in this paper. In principle, if the covariance is stochastic, it would represent additional sources of variation in the investment opportunity and induce extra intertemporal hedging demand terms.

The second term in equation (2.13) reflects the investors' demand for the asset as a vehicle to hedge against "unfavorable" shifts in the investment opportunity set. An "unfavorable" shift in the investment opportunity set variable $x$ is defined as a change in $x$ such that future consumption $c$ will fall for a give level of future wealth. That is, an unfavorable shift is an increase in $x$ if $\partial c/\partial x < 0$ and a decrease in $x$ if $\partial c/\partial x > 0$.

Merton (1973) shows that all risk-averse utility maximizers will attempt to hedge against such shifts in the sense that if $\partial c/\partial x < 0$ ($\partial c/\partial x > 0$), then, ceteris paribus, they will demand more of the $i$th asset, the more positively (negatively) correlated its return is with changes in $x$. Thus, if the ex post opportunity set is less favorable than was anticipated, the investor will expect to be compensated by a higher level of wealth through the positive correlation of the returns. Similarly, if the ex post returns are lower, he will expect a more favorable investment environment.

### 2.4.1. Data

We estimate the risk-return relation between equity returns and their conditional covariances with the innovations in economic fundamentals using a wide variety of stock portfolios. Using portfolios instead of individual stocks reduces the workload to a manageable level and reduces the noise in individual stocks. Based on the market beta, size, and book-to-market characteristics of individual stocks, we form the value-weighted portfolios.[6] We then estimate the intertemporal relation using three sets of portfolios: 100 size/book-to-market, 100 beta/book-to-market, and 100 size/beta portfolios. For the innovations in economic fundamentals, we use the extracted macroeconomic shocks as discussed in Section 2.3.

**Size/book-to-market portfolios**

Similar to a series of papers by Fama and French (1992, 1993, 1995, 1996), we form stock portfolios according to the deciles of the stocks' market capitalization (size) and book-to-market equity ratios (BM) from January 1963 to December 2005. To construct the Size/BM portfolios, in June of each year, we rank all NYSE stocks in CRSP based on their market capitalization (ME). Then, we break NYSE, AMEX, and Nasdaq stocks into 10 size groups based on the breakpoints of the NYSE stock deciles. Finally, we decompose all the NYSE, AMEX, and Nasdaq stocks into 10 BM groups based on the NYSE stock deciles on BM ratios. This generates 100 ($10 \times 10$) Size/BM portfolios of the NYSE/AMEX/Nasdaq stocks.

[6] At an earlier stage of the study, we also used the equal-weighted size/book-to-market, beta/book-to-market, and size/beta portfolios. Since the qualitative results turn out to be very similar to those reported in our tables, we do not present them in the paper. They are available upon request.

**Beta/book-to-market portfolios**

We form 100 stock portfolios according to the deciles of the stocks' market beta and book-to-market equity ratios (BM) from January 1963 to December 2005. Market beta of each stock trading at NYSE, AMEX, and Nasdaq is estimated using one month of daily returns on each stock and the market portfolio. We use the value-weighted average returns of the NYSE/AMEX/Nasdaq stocks (CRSP value-weighted index return) as a proxy for the market portfolio. To construct the Beta/BM portfolios, in June of each year, we rank all the NYSE, AMEX, and Nasdaq stocks (all stocks in CRSP) based on their market betas and then place them into 10 Beta portfolios based on the decile breakpoints. Finally, we decompose all stocks in CRSP into 10 BM groups based on the NYSE stock deciles on BM ratios. This gives 100 ($10 \times 10$) Beta/BM portfolios of the NYSE/AMEX/Nasdaq stocks.

**Size/beta portfolios**

We form 100 stock portfolios according to the deciles of the stocks' market capitalization (size) and market beta from January 1963 to December 2005. Market beta of each stock in CRSP is estimated using one month of daily returns on individual stock and the market portfolio. To construct the Size/Beta portfolios, in June of each year, we rank all NYSE stocks in CRSP based on their market capitalization (ME). Then, we break the NYSE, AMEX, and Nasdaq stocks into 10 size groups based on the breakpoints of the NYSE stock deciles. Finally, we rank all stocks in CRSP based on their market betas and then group them into 10 Beta portfolios based on the decile breakpoints. This generates 100

$(10 \times 10)$ Size/Beta portfolios of the NYSE/AMEX/Nasdaq stocks.

### 2.4.2. Conditional covariance approach

We estimate the conditional covariance between excess returns on each portfolio and the innovations in macroeconomic variables based on the following bivariate GARCH(1,1) specification:

$$R_{i,t+1} = \alpha_0^i + \alpha_1^i R_{i,t} + \varepsilon_{i,t+1}, \tag{2.16}$$

$$x_{t+1} = \alpha_0^x + \alpha_1^x x_t + \varepsilon_{x,t+1}, \tag{2.17}$$

$$\mathbb{E}_t\left[\varepsilon_{i,t+1}^2\right] \equiv \sigma_{i,t+1}^2 = \gamma_0^i + \gamma_1^i \varepsilon_{i,t}^2 + \gamma_2^i \sigma_{i,t}^2, \tag{2.18}$$

$$\mathbb{E}_t\left[\varepsilon_{x,t+1}^2\right] \equiv \sigma_{x,t+1}^2 = \gamma_0^x + \gamma_1^x \varepsilon_{x,t}^2 + \gamma_2^x \sigma_{x,t}^2, \tag{2.19}$$

$$\mathbb{E}_t\left[\varepsilon_{i,t+1}\varepsilon_{x,t+1}\right] \equiv \sigma_{ix,t+1} = \rho_{ix}\sigma_{i,t+1}\sigma_{x,t+1}. \tag{2.20}$$

where $R_{i,t+1}$ and $x_{t+1}$ denote the excess return on portfolio $i$ and the innovations in macroeconomic variables at time $(t+1)$, respectively. First, we use an AR(1) specification to demean the excess returns. Then we define each element of the conditional covariance matrix as a GARCH(1,1) process, where $\mathbb{E}_t[\cdot]$ denotes the conditional expectation operator conditional on time $t$ information. Thus, $\sigma_{i,t+1}^2$ and $\sigma_{x,t+1}^2$ are the time-$t$ conditional variance of portfolio returns and macroeconomic innovations, respectively. $\rho_{i,x}$ is the correlation coefficient and $\sigma_{ix,t+1}$ is time-$t$ conditional covariance between the excess returns on portfolio $i$ and the shocks to macroeconomic variables $x$. The GARCH specifications in equations (2.16) to (2.20) do not arise directly from the ICAPM model, but they provide a close and parsimonious approximation of the form of heteroscedasticity typically encountered with economic time-series data (Bollerslev, Chou, and Kroner (1992) and Bollerslev, Engle, and Nelson (1994)). The specifications are direct multivariate generalizations of univariate GARCH models developed by Engle (1982) and Bollerslev (1986).

We estimate the conditional covariances of each portfolio with the innovations in inflation and real activity using the maximum likelihood method. Using $\varepsilon_t$ and $V_t$ to denote the bivariate demeaned excess return vector and the conditional covariance matrix forecasts,

$$\varepsilon_t = \begin{bmatrix} R_{i,t} - \alpha_0^i - \alpha_1^i R_{i,t-1} \\ x_t - \alpha_0^x - \alpha_1^x x_{t-1} \end{bmatrix}, \quad V_t = \begin{bmatrix} \sigma_{i,t}^2 & \sigma_{ix,t} \\ \sigma_{ix,t} & \sigma_{x,t}^2 \end{bmatrix}, \tag{2.21}$$

we can write the log-likelihood function as

$$\mathcal{L}(\Theta) = -\frac{1}{2}\sum_{t=1}^{N}\left[\ln(2\pi) + \ln|V_t| + \varepsilon_t^\top V_t^{-1}\varepsilon_t\right], \tag{2.22}$$

where $\Theta$ denotes the vector of parameters in the specifications (2.16) to (2.20) and $N$ denotes the number of monthly observations for each series.

### 2.4.3. Estimation results

Panel A (Panel B) in Table 2.4 provides the descriptive statistics on the parameter estimates of the bivariate GARCH model with normal distribution that governs the joint dynamics of the conditional mean and conditional variance of the excess returns on the 100 Size/BM portfolios and innovations in inflation (output).[7] The average AR(1) coefficients of the inflation- and output-related shocks are, respectively, 0.3254 and 0.3282, and statistically significant at the 1% level. These results indicate strong, positive first-order autocorrelation in monthly economic innovations. The average AR(1) coefficient of excess returns on the Size/BM portfolios in Panel A (Panel B) is 0.1137 (0.0014), ranging from -0.0945 (-0.0909) to 0.2966 (0.2921), and 63 (61) of the 100 Size/BM portfolios have an AR(1) coefficient significant at least at the 5% level.

The average ARCH coefficients ($\gamma_1^{inf}$, $\gamma_1^{out}$) of innovations in inflation and output are 0.0976 and 0.1244, respectively, and both are significant at the 1% level. The average GARCH coefficients ($\gamma_2^{inf}$, $\gamma_2^{out}$) of innovations in inflation and output shocks are 0.8762 and 0.8555, respectively, and both are significant at the 1% level. The average ARCH coefficient of the 100 Size/BM portfolios in Panel A (Panel B) is 0.0785 (0.0795), ranging from 0.0168 (0.0165) to 0.1745 (0.1767), and 84 (84) of the 100 portfolios have an ARCH coefficient significant at least at the 5% level. The average GARCH coefficient of the 100 Size/BM portfolios in Panel A (Panel B) is 0.8551 (0.8495), ranging from 0.6399 (0.6147) to 0.9332 (0.9322). All of the Size/BM portfolios have a GARCH coefficient significant at least at the 5% level. The sum of ARCH and GARCH coefficients is close to one, indicating the existence of strong volatility persistence in economic innovations and portfolio returns. Moreover, small standard deviation of the parameter estimates that govern the joint

[7] To save space, we only present the descriptive statistics for the 100 Size/BM portfolios. The results from the Size/Beta and Beta/BM portfolios are qualitatively similar. They are available upon request.

dynamics of the excess portfolio returns and economic innovations provides evidence on the stability of our bivariate GARCH estimation.

The average correlation coefficient between the excess portfolio returns and the innovations in inflation is about -0.1055, ranging from -0.1724 to -0.0504. 98 of the 100 Size/BM portfolios have a negative correlation coefficient significant at least at the 5% level. The average correlation coefficient between the excess portfolio returns and the innovations in output is about 0.0314, ranging from -0.0189 to 0.0967. 83 of the 100 portfolios have a positive correlation coefficient.

We computed the value-weighted average of the conditional covariances between the excess portfolio returns and shocks to inflation and output. We also estimated the conditional covariances between the excess market return and shocks to inflation and output.

The upper (low) panel in Figure 2.2 compares the conditional covariance of excess market returns and shocks to inflation (output) with the value-weighted average of the conditional covariances of excess portfolio returns and shocks to inflation (output). Figure 2.2 shows that the value-weighted average conditional covariance of the Size/BM portfolios is similar to the conditional covariance of the market portfolio. In fact, the correlation between the two time-series series is about 0.93 for the innovations in inflation (upper panel), and it is about 0.90 for the innovations in output (lower panel).

The time-series averages of the conditional covariances of the Size/BM portfolios are similar to their corresponding unconditional covariance estimates. This shows the accuracy and robustness of our conditional covariance estimation. The standard deviations of the conditional covariances are non trivial as compared to the average conditional covariance estimates. Hence, it is important to allow the conditional covariances to vary over time when estimating the risk-return relation between macroeconomic shocks and portfolio returns.[8]

## 2.5. The Risk-Return Relation

We first discuss the econometric methodology for testing the risk-return relation between excess monthly portfolio returns and their conditional covariance with the economic shocks. We then report and discuss the estimation results.

### 2.5.1. Estimating risk-return relation

We estimate the risk-return relation between excess portfolio returns and their covariance with the economic shocks from the following system of equations,

$$R_{i,t+1} = C_i + A_{inf}\omega_{i,inf,t+1} + A_{out}\omega_{i,out,t+1} + e_{i,t+1}, \quad i = 1, 2, \cdots, n, \tag{2.23}$$

where $n$ denotes the number of portfolios and also the number of equations in the estimation, and $\omega_{i,inf,t+1}$ and $\omega_{i,out,t+1}$ are the estimated conditional covariance between excess monthly returns on portfolio $i$ and the inflation- and output-related shocks, respectively. We

[8]To save space, we do not report detailed results on the unconditional covariance estimates, and the mean and standard deviation of the conditional covariance estimates for each Size/BM, Beta/BM, and Size/Beta portfolios. They are available upon request.

constrain the slope coefficients ($A$) to be the same across all portfolios for cross-sectional consistency. We allow the intercept $C_i$ to differ across different portfolios.

We estimate the system of equations using a weighted least square method that allows us to place constraints on coefficients across equations. We compute the $t$-statistics of the parameter estimates accounting for heteroscedasticity and autocorrelation as well as contemporaneous cross-correlations in the errors from different equations. The estimation methodology can be regarded as an extension of the seemingly unrelated regression (SUR) method, proposed by Parks (1967)

Consider a system of $n$ equations, of which the typical $i$th equation is

$$y_i = X_i \beta_i + u_i, \tag{2.24}$$

where $y_i$ is a $N \times 1$ vector of time-series observations on the $i$th dependent variable, $X_i$ is a $N \times k_i$ matrix of observations of $k_i$ independent variables, $\beta_i$ is a $k_i \times 1$ vector of unknown coefficients to be estimated, and $u_i$ is a $N \times 1$ vector of random disturbance terms with mean zero. Parks (1967) proposes an estimation procedure that allows the error term to be both serially and cross-sectionally correlated. In particular, he assumes that the elements of the disturbance vector $u$ follow an AR(1) process:

$$u_{it} = \rho_i u_{it-1} + \varepsilon_{it}, \quad |\rho_i| < 1, \tag{2.25}$$

where $\varepsilon_{it}$ is serially independently but contemporaneously correlated:

$$Cov(\varepsilon_{it}, \varepsilon_{jt}) = \sigma_{ij}, \forall i, j, \quad \text{and} \quad Cov(\varepsilon_{it}, \varepsilon_{js}) = 0, \quad \text{for } s \neq t. \tag{2.26}$$

Equation (2.24) can then be written as

$$y_i = X_i \beta_i + P_i \varepsilon_i, \tag{2.27}$$

with

$$P_i = \begin{bmatrix} (1-\rho_i^2)-1/2 & 0 & 0 & \cdots & 0 \\ \rho_i(1-\rho_i^2)-1/2 & 1 & 0 & \cdots & 0 \\ \rho_i^2(1-\rho_i^2)-1/2 & \rho_i & 1 & \cdots & 0 \\ \vdots & & & & \\ \rho_i^{N-1}(1-\rho_i^2)-1/2 & \rho^{N-2} & \rho^{N-3} & \cdots & 1 \end{bmatrix}. \tag{2.28}$$

Under this setup, Parks presents a consistent and asymptotically efficient three-step estimation technique for the regression coefficients. The first step uses single equation regressions to estimate the parameters of autoregressive model. The second step uses single equation regressions on transformed equations to estimate the contemporaneous covariances. Finally, the Aitken estimator is formed using the estimated covariance,

$$\widehat{b} = \left(X^\top \Omega^{-1} X\right)^{-1} X^\top \Omega^{-1} y, \tag{2.29}$$

where $\Omega \equiv \mathbb{E}[uu^\top]$ denotes the general covariance matrix of the innovation. In our application, we use the aforementioned methodology with the slope coefficients restricted to be the same for all portfolios. In particular, we use the same three-step procedure and the same covariance assumptions as in (2.25) to (2.28) to estimate the covariances and to generate the $t$-statistics for the parameter estimates.

### 2.5.2. Results and discussion

Table 2.5 reports the common slope estimates and the $t$-statistics based on the system of equations (2.23) for the 100 Size/BM, Beta/BM, and Size/Beta portfolios. The results are based on the conditional covariances estimated using a bivariate GARCH model with normal density. Except for the Size/Beta portfolios, the estimates for the conditional covariance between the excess monthly returns and the inflation-related shocks are negative and statistically significant at least at the 5% level from the univariate and bivariate system of equations. The estimates for the conditional covariance between the excess monthly returns and the output-related shocks are positive and statistically significant at least at the 5% level for all portfolios considered in the paper. This result holds when the conditional covariances with both the inflation- and output-related shocks are used in the system of equations.

Our findings can be interpreted within the context of ICAPM. In Merton (1973)'s original setup, when the investment opportunity set is stochastic, investors adjust their investment to hedge against future shifts in the investment opportunity and achieve intertemporal consumption smoothing. If an asset return moves against the shifts in the investment opportunity, investors increase their investment in the asset for its positive role in intertemporal consumption smoothing. In equilibrium, investors are willing to accept a lower expected excess return on this asset for its intertemporal hedging function.

In this paper, one of our states variables is inflation that moves negatively with optimal consumption. Thus, the negative coefficient estimate on the conditional covariance of returns with inflation-related shocks indicates that an increase in a portfolio's covariance with unexpected inflation predicts a lower excess return on the portfolio. In the context of Merton (1973)'s ICAPM, this negative slope estimate suggests that an increase in unexpected inflation predicts a decrease in optimal consumption and hence an unfavorable shift in the investment opportunity set. This generates an increase in intertemporal hedging demand for the portfolio, which in equilibrium reduces the excess return on the portfolio, and hence a negative coefficient on the conditional covariance of returns with unexpected inflation.

The other state variable considered in the paper is real economic activity measured by output or economic growth that moves positively with optimal consumption. Hence, the positive coefficient estimate on the covariance of returns with output-related shocks indicates that an increase in a portfolio's covariance with unexpected economic growth predicts a higher excess return on the portfolio. According to Merton (1973)'s ICAPM, this positive slope estimate suggests that an increase in unexpected growth predicts an increase in optimal consumption and hence a favorable shift in the investment opportunity set. Therefore, a positive correlation of a portfolio's return with unexpected growth reduces intertemporal hedging demand for the portfolio. Intertemporally, an increase in the positive correlation leads to a decrease in the hedging demand, which in equilibrium leads to an increase in the expected excess return on the portfolio, and hence a positive slope estimate for the conditional covariance of returns with innovations in real activity.

We will now briefly explain why the negative relation between expected stock returns and unexpected inflation and the positive relation between expected stock returns and innovations in output are consistent with general economic thoughts.

There are several channels by which inflation surprises may have effects on stock prices.[9] A direct, negative effect could emerge if a positive surprise in announced inflation induces agents to raise their level of expected inflation since a number of studies have found that higher expected inflation depresses stock prices. The explanation for this finding is that investors use inflation-swelled nominal interest rates to capitalize corporate earnings. Higher expected inflation leads to higher nominal interest rates. The anticipation of higher rates in the future causes agents to sell securities immediately, forcing interest rates upward. Higher interest rates then lead to lower stock prices, assuming investors view these assets as substitutes. A second channel by which inflation surprises may affect stock prices occur if agents believe that policymakers react to inflation news. Unexpectedly high inflation may lead to more restrictive policies, which in turn lead to reduced cash flows for firms and lower stock prices. Similarly, if a positive inflation surprise causes agents to revise upward their assessment of future money demand, higher interest rates and lower stock prices may result if agents further expect the Federal Reserve to maintain its previous monetary

[9] See Schwert (1981) for a careful treatment of the inflation announcement.

growth objectives. In any event, all of these potential links suggest that stock prices may be negatively related to surprises in announced measures of inflation.

The positive relation between expected stock returns and innovations in output makes economic sense. Announced increases in real economic activity, if greater than expected, may increase agents' expectations of future growth. Forecasts of higher economic growth should make stocks more attractive and thus cause an immediate jump in share prices.

## 2.6. Robustness Check

To check the robustness of our results, we consider alternative specifications of the conditional covariance and different distributional assumptions for innovations in stock returns and macroeconomic variables.

### 2.6.1. Alternative specifications of the conditional covariance

As shown in Table 2.5, for the Size/Beta portfolios, the coefficient on the conditional covariance between the inflation-related shocks and the excess monthly returns is negative but statistically insignificant. This result seems to be agreeing with the hypothesis in Fama (1981): "*The negative stock return-inflation relations are induced by negative relations between inflation and real activity which in turn are explained by a combination of money demand theory and the quantity theory of money.*" Fama (1981) documents evidence that the negative relations between real stock returns and inflation are the consequence of proxy effects. Stock returns are determined by forecasts of more relevant real variables, and negative stock return-inflations are induced by negative relations between inflation and real activity. Indeed, the inflation- and output-related shocks are negatively correlated, with a correlation coefficient of -0.23.

To check whether there is a separate effect of inflation-related shocks on expected stock returns or the negative relation between stock returns and inflation is the consequence of a proxy effect, we consider an alternative specification of the conditional covariance process.

In Section 2.4, we assume that the conditional variance of economic shocks and portfolio returns follows a GARCH(1,1) process. Since the conditional variance is not directly observed, different specifications of conditional variance could lead to different estimates of conditional covariance, and to different conclusions on the risk-return relation between changes in the aggregate economy and equity returns. In this section, we investigate whether an alternative specification of the conditional covariance influences our results.

The literature has documented substantial evidence suggesting asymmetric impact of downward and upward equity returns on their conditional volatility. [Engle (1990), Nelson (1991), Glosten, Jagannathan, and Runkle (1993), Engle and Ng (1993), Sentana (1995), Zakoian (1994)]. To investigate whether such variation in the conditional variance forecasting specification alters our conclusion, we re-estimate the conditional covariance between economic shocks and portfolio returns using the following alternative specification,[10]

$$R_{i,t+1} = \alpha_0^i + \alpha_1^i R_{i,t} + \varepsilon_{i,t+1}, \tag{2.30}$$

$$x_{t+1} = \alpha_0^x + \alpha_1^x x_t + \varepsilon_{x,t+1}, \tag{2.31}$$

$$\sigma_{i,t+1}^2 = \gamma_0^i + \gamma_1^i \varepsilon_{i,t}^2 + \gamma_2^i \sigma_{i,t}^2 + \gamma_3^i \varepsilon_{i,t}^2 I_{i,t}^-, \tag{2.32}$$

$$\sigma_{x,t+1}^2 = \gamma_0^x + \gamma_1^x \varepsilon_{x,t}^2 + \gamma_2^x \sigma_{x,t}^2 + \gamma_3^x \varepsilon_{x,t}^2 I_{x,t}^-, \tag{2.33}$$

$$\sigma_{ix,t+1} = \rho_{ix} \sigma_{i,t+1} \sigma_{x,t+1}, \tag{2.34}$$

where $I_{i,t}^-$ ($I_{x,t}^-$) is an indicator function that equals one when $\varepsilon_{i,t}$ ($\varepsilon_{x,t}$) is negative and zero otherwise. The conditional volatility parameters $\gamma_3^i$ and $\gamma_3^x$ allow for an asymmetric volatility response to past positive and negative shocks to returns and macroeconomic variables. The parameters in equations (2.30) to (2.34) are estimated by maximizing the log-likelihood function given in equation (2.22).

Table 2.6 presents the common slope coefficients and their $t$-statistics from estimating the system of equations for the 100 Size/BM, Beta/BM, and Size/Beta portfolios. The results are based on the conditional covariances that are estimated using a bivariate GJR-GARCH model with normal density. For all portfolios including the 100 Size/Beta portfolios, the estimates for the conditional covariance between the inflation-related shocks and the excess monthly returns are negative and highly significant. This result holds when

[10]There are a number of specifications available to model the asymmetry in the conditional volatility process. However, there is no consensus in the GARCH literature on which specification is the most appropriate. In this paper, we use the asymmetric GARCH (GJR-GARCH) model of Glosten, Jagannathan, and Runkle (1993).

the conditional covariances with both inflation- and output-related shocks are used in the system of equations. The parameter estimates in Table 2.6 indicate that there is a separate effect of inflation-related shocks on expected stock returns. Hence, the negative stock return-inflation relation is not induced by the negative relation between inflation and real activity.

The qualitative results for return-output relations are very similar to those obtained from the bivariate GARCH(1,1) specification. As shown in Table 2.6, the estimates for the conditional covariance between the output-related shocks and the excess monthly returns are positive and highly significant for all portfolios considered in the paper. This result holds for both the univariate and bivariate system of equations.

### 2.6.2. Alternative distribution functions

In Section 2.4, we assume that the economic shocks and portfolio returns follow a conditional normal distribution. Given the strong evidence on stock return non-normalities, in this section, we consider a more general distribution function for the innovations in returns and macroeconomic variables. We assume that the conditional distribution of the economic shocks and portfolio returns follows a bivariate Student-t density that takes into account tail-thickness in the distribution of innovations in returns and macroeconomic variables. Using $\varepsilon_t$ and $V_t$ to denote the bivariate demeaned excess return vector and the conditional covariance matrix forecasts,

$$\varepsilon_t = \begin{bmatrix} R_{i,t} - \alpha_0^i - \alpha_1^i R_{i,t-1} \\ x_t - \alpha_0^x - \alpha_1^x x_{t-1} \end{bmatrix}, \quad V_t = \begin{bmatrix} \sigma_{i,t}^2 & \sigma_{ix,t} \\ \sigma_{ix,t} & \sigma_{x,t}^2 \end{bmatrix}, \tag{2.35}$$

the bivariate Student-t density is

$$f(\varepsilon_t|\mathcal{F}_{t-1}) = \frac{\Gamma((v+2)/2)}{\pi(v-2)\Gamma(v/2)} |V_t|^{-1/2} \left(1 + \frac{\varepsilon_t^\top V_t^{-1} \varepsilon_t}{v-2}\right)^{-(v+2)/2}, \tag{2.36}$$

where $\mathcal{F}_{t-1}$ denotes the time $(t-1)$ filtration, $\Gamma(a) = \int_0^{+\infty} x^{a-1} e^{-x} dx$ is the gamma function, and $v$ is the degrees of freedom parameter, which controls the tail behavior of the $t$-distribution. Thus, we can write the log-likelihood function as

$$\mathcal{L}(\Theta) = -\frac{1}{2} \sum_{t=1}^{N} \left[ 2 \ln \frac{\pi(v-2)\Gamma(v/2)}{\Gamma((v+2)/2)} + \ln|V_t| + (v+2) \ln \left(1 + \frac{\varepsilon_t^\top V_t^{-1} \varepsilon_t}{v-2}\right) \right], \tag{2.37}$$

where $\Theta$ denotes the vector of parameters in the specifications (2.16) to (2.20) for the GARCH model and (2.30) to (2.34) for the GJR-GARCH model, and $N$ denotes the number of observations for each series.[11]

Table 2.7 reports the common slope coefficients and their $t$-statistics based on the conditional covariances that are estimated using the bivariate GARCH and GJR-GARCH models with Student-t density. In both panels of Table 2.7, we observe a positive and

[11] Bollerslev (1987), Hsieh (1989a,b), and Nelson (1991), among others, use fat-tailed distributions such as the student-$t$ and the generalized error distributions in GARCH model estimations for stock returns and exchange rates.

significant relation between future stock returns and their conditional covariance with the output-related shocks. This findings holds for all portfolios considered in the paper and for both the symmetric and asymmetric GARCH specifications. The significantly positive relation remains the same when the conditional covariances with both inflation- and output-related shocks are used in the system of equations.

The parameter estimates in Table 2.7 indicate a negative and significant relation between future stock returns and their conditional covariance with the inflation-related shocks. The only exception is that when the conditional covariances are estimated using the bivariate GARCH model with Student-t density, although the negative relation remains alive, it becomes statistically insignificant for the Size/Beta portfolios. However, for the Size/BM and Beta/BM portfolios, we find a negative and highly significant relation between expected returns and inflation-related shocks. Furthermore, as shown in Panel B of Table 2.7, when the conditional covariances are estimated using the bivariate GJR-GARCH model with Student-t density, the negative inflation-return relations are significant for all portfolios considered in the paper.

## 2.7. Conclusion

We extend the literature on the risk-return relation between macroeconomic shocks and equity returns in three important ways. First, we use a dynamic factor model to succinctly summarize the information and suppress the noise in many observed macroeconomic series. Second, we exploit the risk-return relation between a wide variety of stock portfolios formed based on market beta, size, and book-to-market characteristics and their conditional covariance with the economic shocks. By doing so, we alleviate the problem of low statistical power caused by focusing narrowly on the risk-return relation of a single market return series. Finally, we allow the conditional covariance between returns and economic shocks to be time-varying. We relax the assumption, often implicitly or explicitly imposed in the literature, that the covariance between security return and the systemic risk factor is a linear function of the systematic risk factor.

The results from the univariate and bivariate system of equations show that equity returns are negatively correlated with their conditional covariance with the inflation-related shocks and positively correlated with their conditional covariance with the output-related shocks. This finding is robust to different portfolio formations, alternative specifications of the conditional covariance, and different distributional assumptions for innovations in returns and macroeconomic variables.

In the context of Merton (1973)'s ICAPM, the negative (positive) slope estimate suggests that an increase in inflation (economic growth) predicts a decrease (increase) in optimal consumption and hence an unfavorable (favorable) shift in the investment opportunity set. Intertemporally, an increase in the covariance of returns with unexpected inflation (unexpected growth) leads to an increase (decrease) in the hedging demand, which in equilibrium decreases (increases) the excess return on the portfolio, and hence a negative (positive) slope estimate for the conditional covariance of returns with innovations in inflation (real activity).

The importance of a negative (positive) and significant inflation-return (output-return) relations is that it may indicate hedging opportunities for investors and that the changes in inflation and real economic activity may be a priced factor. Future research should investigate whether investors earn excess returns for bearing the risk associated with shifts in inflation and output.

Table 2.1

Extracting Systematic Dynamic Factors From Macroeconomic Data

Entries report the estimates and the absolute values of the $t$-statistics (in parentheses) of parameters ($H$) that link each observed data series to the two systematic dynamic factors. Entries under ($H_i$) denote the loadings of each series on the $i$th factor. Entries under $\mathcal{R}^y$ report the measurement error variance estimates and $t$-statistics for each series. The last column ($R^2$) reports the predicted variation of the factors on each series, defined as one minus the ratio of the forecasting error variance over the variance of the original series. The parameters are estimated with maximum likelihood method joint with Kalman filter using macroeconomic series listed below. The macroeconomic data are downloaded from the Federal Reserve Board. The sample period is from January 1963 to December 2005.

| Series | $H_1$ | | $H_2$ | | $\mathcal{R}^y$ | | $R^2$ |
|---|---|---|---|---|---|---|---|
| CPI | 0.330 | ( 27.60 ) | – | – | 0.045 | ( 15.81 ) | 0.944 |
| Core CPI | 0.314 | ( 15.34 ) | – | – | 0.137 | ( 12.31 ) | 0.880 |
| PPI | 0.308 | ( 22.45 ) | – | – | 0.172 | ( 10.77 ) | 0.804 |
| Core PPI | 0.317 | ( 26.98 ) | – | – | 0.106 | ( 19.43 ) | 0.902 |
| PCE Deflator | 0.338 | ( 32.55 ) | – | – | 0.000 | ( 0.00 ) | 0.990 |
| Core PCE Deflator | 0.320 | ( 18.43 ) | – | – | 0.106 | ( 8.35 ) | 0.908 |
| GDP Deflator | 0.326 | ( 27.97 ) | – | – | 0.069 | ( 10.61 ) | 0.947 |
| Non-farm Payrolls | 0.133 | ( 11.72 ) | 0.540 | ( 41.63 ) | 0.000 | ( 0.00 ) | 0.977 |
| Industrial Production | – | – | 0.423 | ( 26.18 ) | 0.254 | ( 12.63 ) | 0.683 |
| Real PCE | – | – | 0.327 | ( 17.50 ) | 0.553 | ( 12.89 ) | 0.382 |
| Real GDP | – | – | 0.419 | ( 17.97 ) | 0.264 | ( 8.05 ) | 0.674 |

Table 2.2
Time Series Dynamics of the Economic Factors
Entries report the parameter estimates and the absolute values of the $t$-statistics (in parentheses) on time-series dynamics of the three economic factors. The dynamics are estimated with maximum likelihood method and Kalman filtering with 11 macroeconomic series. The macroeconomic data are from the Federal Reserve Board. The sample period starts from January 1963 to December 2005.

| Dynamic Factors ($X$) | $\kappa$ in: $dX_t = -\kappa X_t dt + dW_t$ | |
|---|---|---|
| Inflation | 0.067 | 0 |
| | (1.10) | – |
| Real Output | 0.269 | 0.296 |
| | (3.49) | (3.03) |

Table 2.3
Time Series Dynamics of the Economic Shocks
Entries report the descriptive statistics on the macroeconomic shocks defined as the difference between the ex post filtering updates on the states of economy and their ex ante expectations. The absolute values of the $t$-statistics (in parentheses) are for the hypothesis that the mean shock equals zero. The sample period starts from January 1963 to December 2005.

| Statistics | Inflation-related Shock | Output-related Shock |
|---|---|---|
| No. of Observations | 516 | 516 |
| Mean | 0.003 | -0.002 |
| | (0.25) | (0.18) |
| Maximum | 1.072 | 1.424 |
| Minimum | -1.020 | -0.984 |
| Standard Deviation | 0.289 | 0.289 |
| Skewness | 0.153 | 0.691 |
| Kurtosis | 4.105 | 5.945 |

Table 2.4

Maximum Likelihood Estimates of the Bivariate GARCH Model with Normal Distribution

Entries in Panel A (Panel B) report the descriptive statistics on the parameter estimates of the bivariate GARCH model with normal distribution that governs the joint dynamics of the conditional mean and conditional variance of excess value-weighted returns on the 100 Size/BM portfolios and innovations in inflation (output). The sample period is from January 1963 to December 2005.

| Parameter | Mean | Std. Dev. | Median | Minimum | Maximum |
|---|---|---|---|---|---|
| Panel A. Parameters governing the dynamics of innovations in inflation and size/BM portfolios | | | | | |
| $\alpha_0^{inf}$ | 0.0014 | 0.0003 | 0.0014 | 0.0008 | 0.0019 |
| $\alpha_1^{inf}$ | 0.3254 | 0.0024 | 0.3255 | 0.3189 | 0.3306 |
| $\gamma_0^{inf}$ | 0.0023 | 0.0000 | 0.0023 | 0.0022 | 0.0024 |
| $\gamma_1^{inf}$ | 0.0976 | 0.0008 | 0.0976 | 0.0944 | 0.0994 |
| $\gamma_2^{inf}$ | 0.8762 | 0.0011 | 0.8762 | 0.8738 | 0.8792 |
| $\alpha_0^{i}$ | 0.0072 | 0.0020 | 0.0073 | 0.0003 | 0.0116 |
| $\alpha_1^{i}$ | 0.1137 | 0.0844 | 0.1267 | -0.0945 | 0.2966 |
| $\gamma_0^{i}$ | 0.0003 | 0.0002 | 0.0002 | 0.0001 | 0.0010 |
| $\gamma_1^{i}$ | 0.0785 | 0.0315 | 0.0716 | 0.0168 | 0.1745 |
| $\gamma_2^{i}$ | 0.8551 | 0.0469 | 0.8634 | 0.6399 | 0.9332 |
| $\rho_{i,inf}$ | -0.1055 | 0.0235 | -0.1051 | -0.1724 | -0.0504 |
| Panel B. Parameters governing the dynamics of innovations in output and size/BM portfolios | | | | | |
| $\alpha_0^{out}$ | -0.0113 | 0.0001 | -0.0114 | -0.0115 | -0.0109 |
| $\alpha_1^{out}$ | 0.3282 | 0.0012 | 0.3283 | 0.3213 | 0.3319 |
| $\gamma_0^{out}$ | 0.0012 | 0.0000 | 0.0012 | 0.0011 | 0.0013 |
| $\gamma_1^{out}$ | 0.1244 | 0.0011 | 0.1244 | 0.1222 | 0.1273 |
| $\gamma_2^{out}$ | 0.8555 | 0.0014 | 0.8555 | 0.8523 | 0.8588 |
| $\alpha_0^{i}$ | 0.0071 | 0.0020 | 0.0072 | 0.0004 | 0.0114 |
| $\alpha_1^{i}$ | 0.1148 | 0.0816 | 0.1260 | -0.0909 | 0.2921 |
| $\gamma_0^{i}$ | 0.0003 | 0.0002 | 0.0002 | 0.0011 | 0.0011 |
| $\gamma_1^{i}$ | 0.0795 | 0.0319 | 0.0737 | 0.0165 | 0.1767 |
| $\gamma_2^{i}$ | 0.8495 | 0.0494 | 0.8568 | 0.6147 | 0.9322 |
| $\rho_{i,out}$ | 0.0314 | 0.0255 | 0.0278 | -0.0189 | 0.0967 |

Table 2.5
The risk-return relation with cross-sectional consistency: Bivariate GARCH Model with Normal Distribution
Entries report the common slope estimates and the absolute value of the t-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A_{inf}\omega_{i,inf,t+1} + A_{out}\omega_{i,out,t+1} + e_{i,t+1}, \quad i = 1,2,\cdots,n,$$

where $n$ denotes the number of portfolios and also the number of equations in the estimation, and $\omega_{i,inf,t+1}$ and $\omega_{i,out,t+1}$ are the estimated conditional covariance between excess monthly returns on portfolio $i$ and the inflation- and output-related shocks, respectively. The conditional covariances are estimated using the bivariate GARCH model with Normal distribution. The results are based on the monthly value-weighted returns on the 100 Size/BM, 100 Beta/BM, and 100 Size/Beta portfolios from January 1963 to December 2005.

| Portfolios | $A_{inf}$ | | $A_{out}$ | |
|---|---|---|---|---|
| 100 Size/BM | -1.7392 | ( 3.30 ) | — | — |
| 100 Size/BM | — | — | 3.0548 | (3.14 ) |
| 100 Size/BM | -1.4915 | ( 2.72 ) | 1.9859 | ( 2.01 ) |
| 100 Beta/BM | -1.3462 | ( 2.32 ) | — | — |
| 100 Beta/BM | — | — | 2.2236 | (2.30 ) |
| 100 Beta/BM | -1.1604 | ( 1.96 ) | 1.6106 | ( 1.98 ) |
| 100 Size/Beta | -0.3514 | ( 0.59) | — | — |
| 100 Size/Beta | — | — | 2.5265 | (2.30) |
| 100 Size/Beta | -0.1717 | ( 0.28 ) | 2.0927 | ( 1.90 ) |

Table 2.6
The risk-return relation with cross-sectional consistency: Bivariate GJR-GARCH Model with Normal Distribution
Entries report the common slope estimates and the absolute value of the t-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A_{inf}\omega_{i,inf,t+1} + A_{out}\omega_{i,out,t+1} + e_{i,t+1}, \quad i = 1, 2, \cdots, n,$$

where $n$ denotes the number of portfolios and also the number of equations in the estimation, and $\omega_{i,inf,t+1}$ and $\omega_{i,out,t+1}$ are the estimated conditional covariance between excess monthly returns on portfolio $i$ and the inflation- and output-related shocks, respectively. The conditional covariances are estimated using the bivariate GJR-GARCH model with Normal distribution. The results are based on the monthly value-weighted returns on the 100 Size/BM, 100 Beta/BM, and 100 Size/Beta portfolios from January 1963 to December 2005.

| Portfolios | $A_{inf}$ | | $A_{out}$ | |
|---|---|---|---|---|
| 100 Size/BM | -2.3680 | ( 6.33 ) | — | — |
| 100 Size/BM | — | — | 3.8325 | (4.68 ) |
| 100 Size/BM | -2.2142 | ( 4.97 ) | 1.5703 | ( 2.13 ) |
| 100 Beta/BM | -3.0128 | ( 6.73 ) | — | — |
| 100 Beta/BM | — | — | 5.0311 | (5.70 ) |
| 100 Beta/BM | -2.4803 | ( 5.02 ) | 3.3219 | ( 3.50 ) |
| 100 Size/Beta | -1.2182 | ( 3.15) | — | — |
| 100 Size/Beta | — | — | 3.2136 | (3.48) |
| 100 Size/Beta | -1.0480 | ( 2.35 ) | 2.0217 | ( 1.98 ) |

Table 2.7
The risk-return relation with cross-sectional consistency: Student-t Distribution
Entries report the common slope estimates and the absolute value of the t-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A_{inf}\omega_{i,inf,t+1} + A_{out}\omega_{i,out,t+1} + e_{i,t+1}, \quad i = 1, 2, \cdots, n,$$

where $n$ denotes the number of portfolios and also the number of equations in the estimation, and $\omega_{i,inf,t+1}$ and $\omega_{i,out,t+1}$ are the estimated conditional covariance between excess monthly returns on portfolio $i$ and the inflation- and output-related shocks, respectively. The conditional covariances in Panel A are estimated using the bivariate GARCH Model with Student-t distribution. The conditional covariances in Panel B are estimated using the bivariate GJR-GARCH Model with Student-t distribution. The results are based on the monthly value-weighted returns on the 100 Size/BM, 100 Beta/BM, and 100 Size/Beta portfolios from January 1963 to December 2005.

| Portfolios | $A_{inf}$ | | $A_{out}$ | |
|---|---|---|---|---|
| Panel A. Bivariate GARCH with Student-t Density | | | | |
| 100 Size/BM | -1.6981 | ( 3.26 ) | — | — |
| 100 Size/BM | — | — | 3.1009 | (3.12 ) |
| 100 Size/BM | -1.4591 | ( 2.70 ) | 2.0511 | ( 2.04 ) |
| 100 Beta/BM | -1.5861 | ( 2.76 ) | — | — |
| 100 Beta/BM | — | — | 2.3138 | (2.40 ) |
| 100 Beta/BM | -1.3942 | ( 2.36 ) | 1.5306 | ( 1.99 ) |
| 100 Size/Beta | -0.6109 | ( 1.02 ) | — | — |
| 100 Size/Beta | — | — | 2.0701 | (2.31) |
| 100 Size/Beta | -0.5103 | ( 0.86 ) | 1.4546 | ( 1.96 ) |
| Panel B. Bivariate GJR-GARCH with Student-t Density | | | | |
| 100 Size/BM | -2.5959 | ( 5.40 ) | — | — |
| 100 Size/BM | — | — | 3.9769 | (3.90 ) |
| 100 Size/BM | -2.4351 | ( 4.74 ) | 1.8606 | ( 2.11 ) |
| 100 Beta/BM | -2.9995 | ( 5.33 ) | — | — |
| 100 Beta/BM | — | — | 4.5177 | ( 4.44 ) |
| 100 Beta/BM | -2.6013 | ( 4.45 ) | 2.9095 | ( 2.83 ) |
| 100 Size/Beta | -1.4185 | ( 2.72 ) | — | — |
| 100 Size/Beta | — | — | 3.6253 | ( 3.17 ) |
| 100 Size/Beta | -1.2624 | ( 2.30 ) | 2.2532 | ( 2.02 ) |

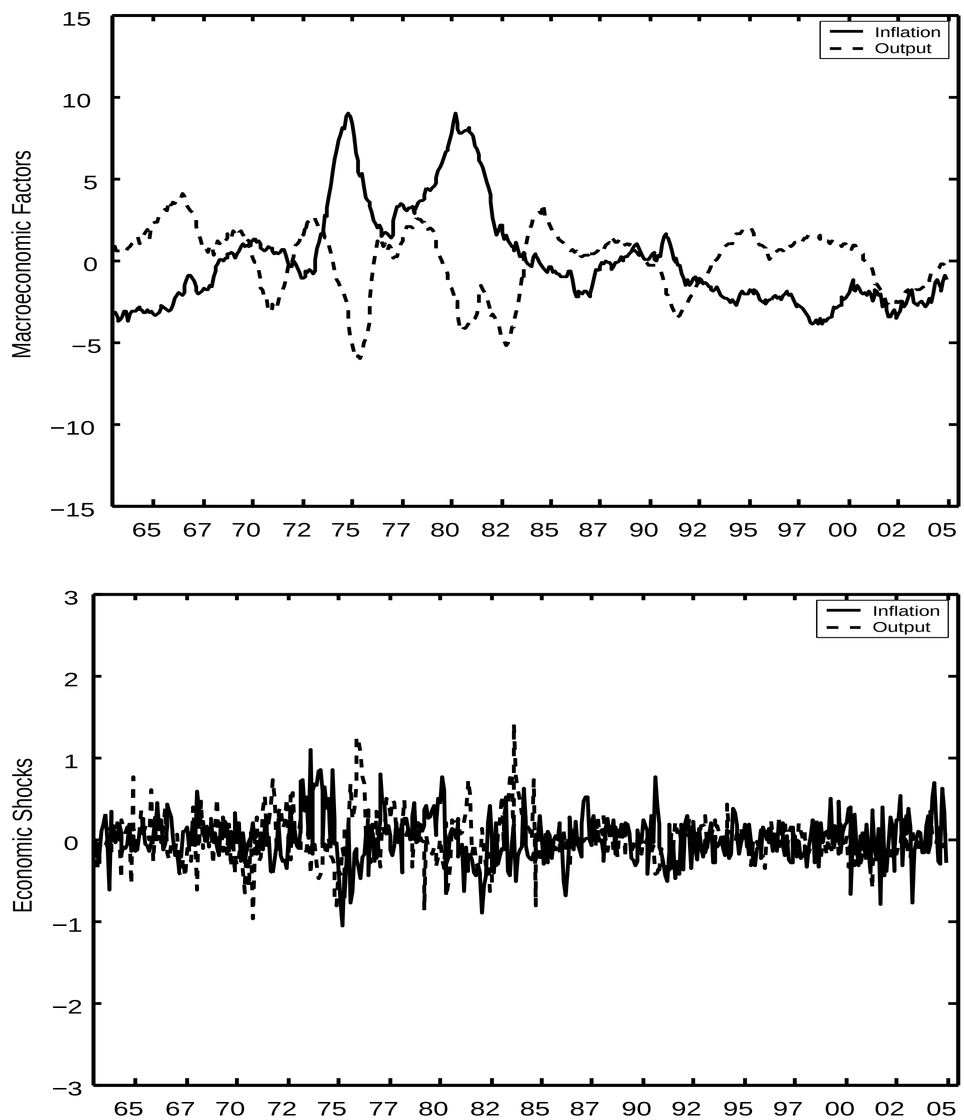


Fig. 2.1. **Dynamic Economic Factors and Shocks:** The solid line in the upper panel denotes the time series of the extracted inflation factor and the dashed line denotes the time series of the extracted real output growth factor. The solid line in the lower panel denotes the time series of the inferred inflation-related shock and the dashed line denotes the time series of the shock related to the real economy.

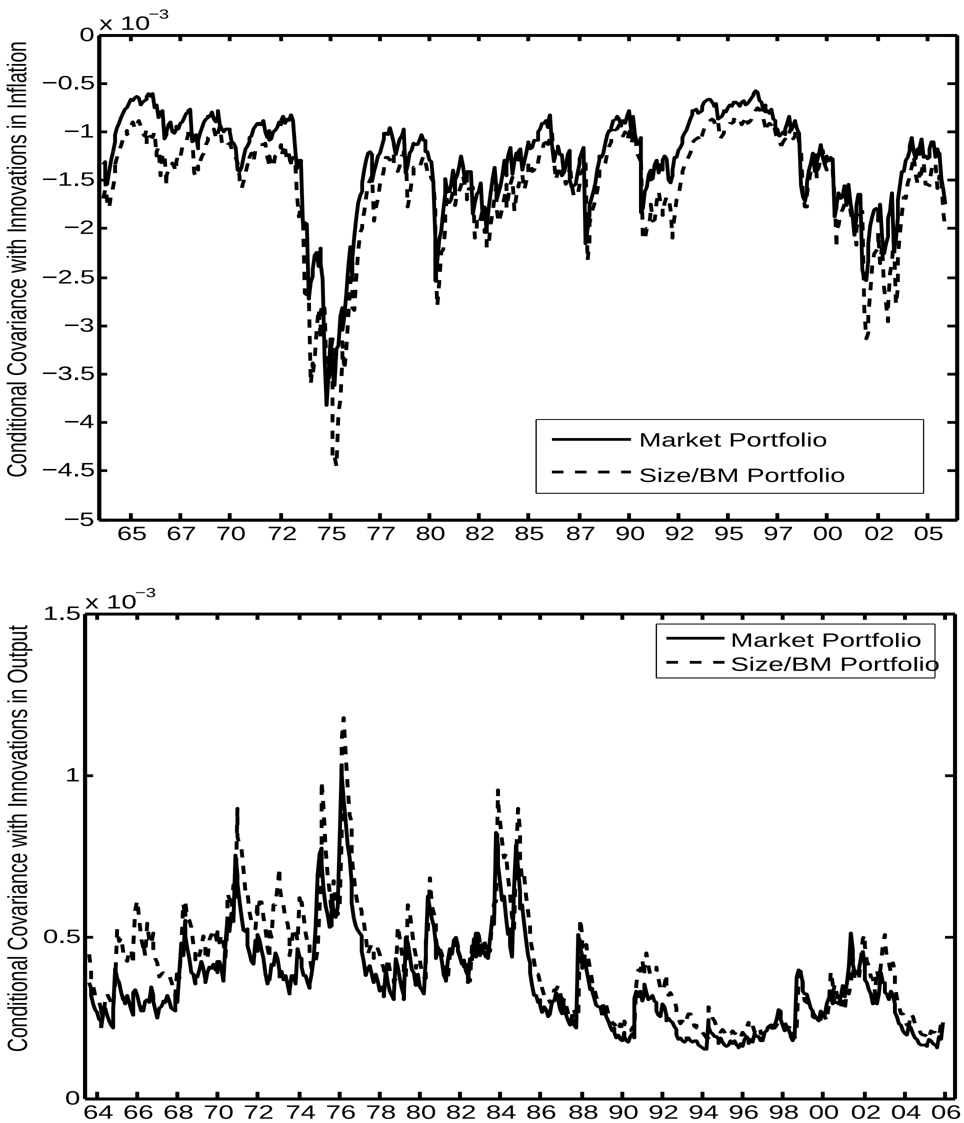


Fig. 2.2. **Conditional covariance of the market portfolio vs the value-weighted average conditional covariance:** In the upper (lower) panel, the solid line denotes the conditional covariance between the excess market returns and innovations in inflation (output), and the dashed line denotes the value-weighted average conditional covariance between the excess returns on the 100 Size/BM portfolios and innovations in inflation (output).

# Part III

# Imports, Exports, and the Relation between Currency Risk Exposure and Expected Stock Returns

## 3.1. Introduction

With increasing global market integration, a firm's performance depends on not only the domestic market fluctuation but also the international market condition. Exchange rate fluctuation is widely believed to affect the functioning and profitability of a firm. What is not so clear is the relation between fluctuations in exchange rate and the stock prices of a firm. In what is now commonly referred to as the exchange rate exposure of a firm, the basic question that the literature grapples with is: Does a firm's share value fluctuate with the exchange rate? If the answer is affirmative, we say that the firm is "exposed" to the exchange rate risk. This exchange rate exposure leads further to two important questions: (1) What are the sources or determinants of the exchange rate exposure? (2) How do companies with different exchange rate exposures differ in the expected returns on their stocks? The former question traces the exposure to economic fundamentals and the business composition of a company. The latter strives to determine whether stock market investors have preferences for the exchange rate risk exposure and how the market prices the risk exposure.

In this paper, we attempt to answer the above questions in light of the experience of US industries. We say that a company or an industry in the US has a positive currency exposure when its stock returns increase with the appreciation of the dollar, the home currency. When we regress stock returns against returns on an aggregate dollar index, we obtain currency risk exposure estimates that vary widely across different industries, in both magnitudes and directions. For example, we find that industries under the title of "boot and shoe cut stocking," "steel investment foundaries," and "space vehicle equipment" generate highly negative currency exposure estimates, and industries under "household refrigerator and freezer" and "men's and boy's underwear " generate highly positive currency exposure estimates. We also find that the currency exposure estimates can vary greatly even within the same broad sector classification. For example, while space vehicle equipment under the defense sector generates highly negative exposure estimates, the "ordnance and necessary accessories" industry under the same defense sector generates highly positive exposure estimates.

To explore the underlying source of the cross-sectional variation, we hypothesize that profits from import- and export-oriented companies should have opposite exchange rate exposures. When left unhedged, these opposite exposures will show up in stock returns. To test this hypothesis, we regress cross-sectionally the currency risk exposure estimates on each industry against the industry's imports volume and the exports volume, each normalized by the market capitalization of the industry. The regression identifies a significantly positive linkage with the imports volume, but a significantly negative linkage with the exports volume. On average, dollar appreciation helps the stock performance of import-oriented companies, but hurts the stock performance of export-oriented companies.

Economic theory tells us that dollar appreciation makes exports more expensive and hence hurts the demand for exports. Reduced demand hurts the sales and thus profitability of the company. On the other hand, dollar appreciation reduces the cost of imports and hence increases the profitability of an import-oriented company.

To gauge the market pricing of the currency risk, we first perform rolling window estimation on the currency risk exposure, and then regress next period's stock returns cross-sectionally against their current currency risk exposures. The time series average of the slope coefficient is negative, but not statistically significant. We attribute the low statistical significance to potentially large errors in the currency risk exposure estimates, and propose to enhance the risk exposure identification by exploiting the information content in the annual imports and exports data for each industry. We extract one risk exposure estimate by combining the information from the stock return regression with the information in the imports and exports volume. With the enhanced identification on risk exposure, we obtain a significantly negative estimate on the market price of the currency risk. The negative estimate suggests that on average, import-oriented companies generate lower returns than export-oriented companies.

Intuitively, our finding on the negative market price of currency risk suggests that dollar appreciation is bad for the US economy. Since import-oriented companies benefit from dollar appreciation, these companies act as natural hedges against the economic risk. As a result, investors are willing to accept a lower expected return on these companies.

The rest of the paper is organized as follows. The next section reviews the literature that forms the background of our study. Section 3.3 describes the data. Section 3.4 estimates currency beta. Section 3.5 studies sources of currency risk exposure. Section 3.6 identifies currency risk premium. Section 3.7 concludes.

## 3.2. Background

Identifying the currency exposure of different firms, industries, or economies has been a perennial topic in the academic literature. For example, Philippe (1990) examines 287 US multinationals during 1981–1987 and finds 15% of the firms to have significant exposures. Bodnar and Gentry (1993) examine industries from the US, Canada, and Japan during 1979-1988 and find 20% to 35% of the industries to have significant risk exposures. Amihud (1994) examines 32 largest US exporting firms during 1982–1988 but finds no significant exposure. Dominguez and Tesar (2001) examine a set of non-US industrialized countries over the period 1980–1999 and find large cross-country differences. For example, they find that a large fraction of Japanese firms have exposures to weekly movements in exchange rates, but Chilean firms show very weak exposures.

It is understandable that different firms, industries, or economies have different currency exposures. Interestingly, earlier studies often try to select a more homogeneous sample, e.g., firms with large international business exposures and large exports, in the hope of obtaining more uniform currency exposure estimates. In this paper, we do not shun away from the cross-sectional heterogeneity in currency exposure, but instead regard it as a natural outcome of heterogeneity in business operations, and a key information source in identifying the market price of currency risk.

When examining the fundamental sources of currency exposures, many studies direct the attention to the "openness" of a firm, an industry, or an economy. Philippe (1990) uses the share of foreign sales in total sales as a measure for openness and find that the currency exposure is significantly positively related to the share of foreign sales. Griffin and Stulz (2001) examine the hypothesis that industry competitiveness across countries is an important explanation for exchange rate exposure, but they do not find supporting evidence among US industries. Dominguez and Tesar (2006) use the aggregate bilateral trade flows with the US as a measure of openness for the non-US industrialized countries. They find only a weak link between the openness measure and the exchange rate exposure. He and Ng (1998) find that high exchange rate exposure is related to high exports for Japanese multinationals.

In this paper, we argue that it is not the aggregate openness that matters for currency risk exposure. It is the direction or imbalance of openness that generates currency exposure. A firm can be very open in terms of international trade, but can still minimize its currency exposure by balancing imports with exports. Furthermore, an import-driven firm and an export-driven firm may both have strong currency exposures, but their exposures are unlikely of the same direction. Our empirical findings further confirm our conjecture and show that import-oriented US firms tend to react positively to dollar appreciation whereas export-oriented companies tend to react negatively.

We do not stop at finding the currency risk exposure and relating the cross-sectional variation in the exposure estimates to the industry's differences in imports and exports activities. Instead, we make use of this finding to further enhance the identification of the currency risk exposure. With the enhanced identification, we estimate how industries with different currency exposures differ in expected excess returns, and find that the market charges a significantly negative risk premium on positive currency risk exposure.

A large stream of literature also studies the market pricing of the exchange rate risk, but often with confusing results. For example, Philippe (1991) uses a sample of US firms to show that currency risk exposures vary systematically across different industries, but he does not find any significant pricing for the currency risk exposure. Bernard Dumas (1995) and Giorgio De Santis (1998) study the currency pricing in the framework of an international asset pricing model, where country portfolio returns are related to the return on a world portfolio and returns on several foreign currencies. In a similar framework, Francesca Carrieri (forthcoming) study whether currency risks in emerging market are priced and whether they have spillover effects on the developed markets. A key feature of these studies is their reliance on the *intertemporal* variation in the expected returns of the country portfolios and the conditional covariances between these portfolio returns and the risk factors. In this paper, we argue that the currency exposures vary much more cross-sectionally than intertemporally. Different types of industries simply have different business operations and hence different risk exposures. By contract, as the industry classification largely stay the same over time, the risk exposure of an industry cannot vary too much over time. The same argument holds for a developed economies. Unless an economy is going through large structural transformations, we do not expect the aggregate currency exposure of the economy to vary too much over time. Therefore, it is much more efficient to identify the market pricing of risk factors relying the cross-sectional variation than on the intertemporal variation.

# 3.3. Data

Our analysis involves four broad data sources. To study the currency risk exposure of US firms, we build a dollar index, and we relate the dollar return to returns on US stocks. To explore the sources of the exposure, we obtain imports and exports data on different industries. We also control our risk exposure analysis by incorporating standard market risk factors.

## 3.3.1. The dollar index

We relate stock returns in the US to returns on a dollar index. The dollar index is a weighted average of foreign exchange values of the US dollar against the currencies of a large group of major US trading partners. The index weights vary over time and are derived from US export shares and from US and foreign import shares. Monthly data for the dollar index are available from the Federal Reserve bank of Atlanta statistical release, at *http://www.frbatlanta.org/econ_rd/dol_index/di_index.cfm*. The sample period for our analysis is from January 1973 to December 2001.

During our sample period, the dollar has shown a steady appreciating trend, except the decline in the late 1980s. The right panel shows that log returns on the index can be very volatile, with a monthly range from -4.175% to 4.243%. Table 3.1 reports the summary statistics of the monthly returns on the dollar index under $R^{fx}$. The log returns have an annualized mean estimate of 4.566%, and an annualized standard deviation estimate of 4.456%. The monthly return series show a first-order autocorrelation of 0.347. The return series show little skewness or excess kurtosis. In the column under $ER^{fx}$, we also report the summary statistics of the log excess return on the dollar index over the Treasury bill rate. The excess return has an annualized mean of $-1.995\%$ and an annualized standard deviation of 4.4%.

The left panel plots the time series of the weighted average dollar index. The right panel plots the monthly returns on the dollar index.

### 3.3.2. Stock market risk factors

To properly measure the currency risk exposure of US stocks, we control for systematic risk factors identified from the stock market, including the excess return on the market portfolio over the Treasury bill rate ($ER^{mkt}$), and the size ($SMB$) and book to market ($HML$) risk factors identified by Fama and French (1993). Time series on these risk factors, as well as the Treasury bill rates, are all made available on Kenneth French's online data library at *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*.

The market portfolio return is constructed as the value-weight return on all NYSE, Amex, and Nasdaq stocks. To construct the size and book-to-market factors, Fama and French (1993) first construct six portfolios according to the rankings on market capitalizations ($ME$) and book-to-market equity ratios. In June of each year, they rank all NYSE stocks in the Center for Research in Security Prices (CRSP) at the University of Chicago based on the market capitalization. Then, they use the median NYSE size to split NYSE, Amex, and Nasdaq stocks into two groups, small and big. They also break NYSE, Amex, and Nasdaq stocks into three book-to-market groups based on the breakpoints for bottom 30%, middle 40%, and top 30% of the ranked values of *BM* for NYSE stocks. They construct the *SMB* factor as the difference between the return on the portfolio of small size stocks and the return on the portfolio of large size stocks, and the *HML* factor as the difference between the return on the portfolio of high book-to-market stocks and the return on the portfolio of low book-to-market stocks. In a series of papers, Fama and French (1993, 1995, 1996) document the importance of these two factors.

In Table 3.1, we report the summary statistics of the three risk factors and the risk-free rate. We also report the summary statistics of the excess return on the dollar index over the Treasury bill rate under $ER^{fx}$. Over our sample period, the market portfolio has an annualized excess return of 5.886% over the Treasury rate. By contract, the excess return on negative at $-1.995\%$ on the dollar index. The size and book-to-market portfolios both generate positive excess returns at 2.235% and 5.587%, respectively. The Treasury rate has a sample average of 6.562% during our sample period. The excess return on the market portfolio has an annualized standard deviation of 16.327%, close to four times larger than that on the dollar index. The standard deviation estimates on *SML* and *HML* are smaller at 11.812% and 11.229%, respectively. The autocorrelation estimates on the returns on the stock market risk factors are all much smaller than the estimate on the dollar index returns.

### 3.3.3. Import and export data

We obtain the annual US import and export data by four-digit SIC coded industries. The data from 1972 to 1988 are compiled by Robert Feenstra and are made publicly available at the Center for International Data at University of California, Davis at the following web address:

*http://cid.econ.ucdavis.edu/usixd/usixd4sic.html*.

The data from 1989 to 2001 are updated and maintained by Peter Schott and are made publicly available at Yale University at the following web address:

*http://www.som.yale.edu/faculty/pks4/sub_international.htm*

The import and export data cover manufacturing industries with the four-digit SIC code starting with either 2 or 3. There are 488 unique SIC codes in the original data set. To be included in the study, each industry must have at least three observations on the import and export measures and at least 24 monthly industry portfolio returns. We lose 86 industries because of the restrictions. The import is defined as the total of merchandize that has physically cleared through Customs either entering consumption channels immediately or entering after withdrawal for consumption from bonded warehouses under Customs custody or from Foreign Trade Zones. The export is defined as the selling price, or cost if not sold, including inland freight, insurance, and other charges to the US port of export, but excluding unconditional discounts and commissions. See Feenstra (1996, 1997) and Feenstra, Romalis, and Schott (2002) for a detailed documentation of the data.

Table 3.2 reports the summary statistics of the imports (IM) and exports (EX), both in millions of dollars. Since the observation is on a panel of 402 industries over 30 years, we summarize the behavior of the data in three different ways. In panel A, we first take the time-series average on each series and then report the cross-sectional statistics of the time-series averages. Thus, the statistics in panel measure the cross-sectional variation of the average trade quantities across different industries. In panel B, we average the trade quantities cross-sectionally at each year, and then report the time-series statistics on the average trade quantities. The statistics reflect the time-series variation of the average trade quantities in US firms. In the panel C, we first measure the time-series statistics of each series and then report the cross-sectional average of these time-series statistics. Thus, the numbers reflect the time-series statistics of a typical industry.

Panel A shows that the average imports and exports vary greatly from one industry to another. The imports vary from 82 thousand dollars to 51.78 million dollars, and the exports vary from 168 thousand dollars to 14.99 million dollars. The cross-sectional distributions of imports and exports show large skewness and kurtosis. To obtain better distributional behaviors, we also report the statistics on the natural logarithms of the imports (ln(IM)) and exports (ln(EX)). The time-series averages of the log imports vary from $-3.073$ to 10.683, with a cross-sectional standard deviation of 1.869. The time-series averages of the log exports vary from $-1.845$ to 9.592, with a cross-sectional standard deviation of 1.853. The cross-sectional distributions of the log imports and log exports are much closer to be normally distributed, with small skewness and kurtosis estimates.

In contrast to the large cross-sectional variation, panel B shows that the time-series variations of the average imports and exports are much smaller. The time-series standard deviation estimates for the cross-sectional averages of log imports and log exports are at 0.877 and 0.892, respectively, less than half of the corresponding time-series standard deviation estimates. When we look at the average time-series statistics for each industry in panel C, we find that the average standard deviations estimates are even smaller at 0.381 for log imports and 0.276 for log exports.

To control for the size differences for different industries, we also compute the aggregate market capitalization (ME) for each industry. The market capitalization for each firm is computed as the shares outstanding multiplied by the share price, both of which are available from CRSP. We aggregate the market capitalization of all firms within each industry, and we normalize the imports and exports of an industry in year $t$ by the industry's aggregate market capitalization. In Table 3.2, we report the summary statistics on the logarithm of the market-capitalization normalized imports and exports under the two columns titled "ln(IM/ME)" and "ln(EX/ME))," respectively. With the normalization, the cross-sectional standard deviations become even larger at 2.237 for imports and 1.878 for exports; yet, the time-series standard deviation estimates for the cross-sectional averages in panel B become much smaller at 0.119 for imports and 0.11 for exports. The cross-sectional variation estimates are 20 times larger than the time-series variation estimates. The cross-sectional averages of the time-series standard deviation estimates for each industry in panel C are at 0.342 for normalized imports and 0.307 for normalized exports. Both numbers are comparable to the estimates on the log imports and exports without normalization, but are much smaller than the corresponding cross-sectional standard deviation estimates.

Thus, regardless of how we measure and scale the imports and exports quantities, we find much large cross-sectional variation across different industries than time-series variation over different time periods. The different magnitudes of variation along the two dimensions suggest that different industries can differ dramatically from one to another in their respective international trading activities, but that the interactional trading activities for an industry and for the US economy as a whole are relatively stable over time.

### 3.3.4. Stock returns on industry portfolios

Corresponding to imports and exports for each industry defined by the four-digit SIC code, we also compute the monthly stock returns for each industry. Stock returns data are available from CRSP. We assign each stock to a four-digit SIC industry. At each year $t$, we use the four-digit Compustat SIC code of the stock for the fiscal year ending in calendar year $t-1$. Whenever the Compustat SIC code is not available, we use the CRSP SIC code for June of year $t$. Then, we construct equal-weighted industry portfolios at the beginning of July of year $t$ and rebalance the portfolios on an annual basis. To be included in an industry portfolio in year $t$, a stock must have return data for July of year $t$ and market capitalization for December of year $t-1$. Once we have formed the industry portfolio, we compute the monthly excess returns on each portfolio, defined as the portfolio return minus the Treasury bill rate of the corresponding month.

The last column in Table 3.2 reports the summary statistics of the industry portfolio excess returns (ER). Different from the trade data, the industry portfolio excess returns show both large cross-sectional variation and even larger time-series variation.

## 3.4. Measuring the Dollar Exposure of US Industries

To gauge how stock returns from different industries vary with the dollar index, we perform the following time-series regression on each industry portfolio $i$,

$$ER_t^i = \beta_{i0} + \beta_i^{fx} ER_t^{fx} + \beta_i^{mkt} ER_t^{mkt} + \beta_i^{smb} SMB_t + \beta_i^{hml} HML_t + e_t^i, \tag{3.1}$$

where $ER_t^i$ denotes the time-$t$ monthly log excess return on the $i$-th industry portfolio, $ER_t^{fx}$ denotes the time-$t$ monthly log excess return on the dollar index, $ER_t^{mkt}$ denotes the time-$t$ excess return on the market portfolio, and $SMB_t$ and $HML_t$ denote the monthly return series on the size and book-to-market portfolios, respectively. Thus, the slope coefficient $\beta_i^{fx}$ measures the dollar risk exposure of the $i$-th industry portfolio while controlling for variations in the market, size, and book-to-market risk factors.

We repeat this estimation for each of the 402 industries over the whole sample period from February 1973 to December 2001. Table 3.3 reports in panel A the cross-sectional statistics of the full-sample estimates and $t$-statistics on the slope coefficients. The last column reports the statistics on the R-squares of the regressions. The most interesting to us is the estimates on $\beta^{fx}$, which measures the dollar exposure of different industry portfolio returns while controlling for variations in the three stock market risk factors. The cross-sectional average of the estimates on $\beta^{fx}$ is very small, so is the average $t$-statistics. The small average estimate is consistent with the often insignificant findings in the literature when one regress the market aggregate returns on the dollar index returns. Nevertheless, the dollar exposure estimates show large cross-sectional variation, ranging from $-2.417$ to 1.799. The $t$-statistics range from $-2.692$ to 3.134. The cross-sectional standard deviation of the dollar exposure estimates is 0.629. Figure 3.1 plots the histogram of dollar exposure estimates and the $t$-statistics. Out of the 402 industries, 182 of them have negative dollar exposure estimates with 16 of them significant at the 10% level, and 220 of them have positive dollar exposure estimates, with 33 significant at the 10% level.

When we look into the descriptions of the different industries and their dollar exposure estimates, we find that industries under the title of "boot and shoe cut stocking," "steel investment foundaries," and "space vehicle equipment" generate highly negative currency exposure estimates, but that industries under "household refrigerator and freezer" and "men's and boy's underwear " generate highly positive currency exposure estimates. The currency exposure estimates can vary greatly even within the same broad sector classification. For example, while space vehicle equipment under the defense sector generates highly negative exposure estimates, the "ordnance and necessary accessories" industry under the same defense sector generates highly positive exposure estimates.

For the controlling risk factors, the market beta estimates ($\beta^{mkt}$) average around one as expected. The cross-sectional standard deviation of the estimates is also relatively small at 0.28. The average exposure estimates on the *SMB* and *HML* risk factors are also positive and significant, but with larger cross-sectional standard deviations at 0.546 for *SMB* and 0.484 for *HML*.

To analyze the intertemporal stability of the risk exposure estimates, we also perform rolling window estimation on equation 3.1. For each industry, we repeat the estimation each year in July of each year with a rolling window of ten years. By requiring that within each ten-year rolling window, we have at least 3 annual observations on imports and exports and 24 monthly observations on industry portfolio returns, the number of industries declines from 402 t0 375. Panel B of Table 3.3 reports the cross-sectional statistics on the time-series averages of the slope estimates. The statistics are very much similar to those on the full-sample estimates in Panel A, showing that the rolling-window estimation generates sensible results.

In panel C of Table 3.3, we report the time-series statistics of the cross-sectional averages of the slope estimates across the different industries. The time-series standard deviation of the average dollar exposure is about ten times smaller than the cross-sectional standard deviation of the full-sample estimates or time-series averages of the rolling-window estimates. The much smaller time-series variation is partly due to the smoothing effect of the rolling window, but it also reflects the intertemporal stability of the dollar exposure for the average economy. When we calculate the cross-sectional averages of the time-series statistics in panel D, the average time-series standard deviation for each industry is less than half of the cross-sectional standard deviation, showing that the dollar exposure of each industry is also relatively stable over time.

## 3.5. Tracing Dollar Exposure to Importing and Exporting Activities

When we regress industry portfolio returns on dollar index returns, we find that the average dollar exposure is small, but that the exposure estimates show large cross-sectional variation. These cross-sectional variations can either be due to sample variations (e.g., standard errors in the coefficient estimates), or due to fundamental differences in the dollar risk exposures. The intertemporal stability of the rolling-window estimates suggests that the cross-sectional variation cannot come all from estimation error. The important question is then: Where does the dollar exposure difference come from?

One common conjecture in the literature is that currency exposure is linked to the openness of the economy (or firm). For example, Dominguez and Tesar (2006) use bilateral trade to proxy for the openness of an economy. We agree that the degree of openness is important for currency exposure. A totally closed economy or a firm with no international trade should be little affected by exchange rate movements. However, we argue that the direction or asymmetry of the international trade is the more relevant source for exchange rate exposure. A firm that balances imports with exports can have little currency exposure regardless of the aggregate quantity of the international trade. The direction of the currency exposure depends on whether the firm is more export driven or import driven.

To test our hypothesis, we regress cross-sectionally the full-sample dollar exposure estimates ($\beta^{fx}$) on the time-series averages of the imports and exports of the corresponding industry. We scale imports and exports by the market capitalization of the corresponding industry to control for the size effect, and we further take natural logs on the scaled quantity to obtain better distributional behaviors. The regression estimates and $t$-statistics (in parentheses) are as follows,

$$\begin{array}{ccccccccc} \beta_i^{fx} & = & 0.0394 & + & 0.0583 & \ln(IM/ME)_i & -0.0536 & \ln(EX/ME)_i + e_i, & R^2 = 1.34\%. \\ & & (0.92) & & (2.68) & & (-1.93) & & \end{array} \tag{3.2}$$

The adjusted R-square of the cross-sectional regression over 402 industries is relatively low at 1.34%, indicating that a large proportion of the dollar exposures cannot be explained by the average imports and exports activities. Nevertheless, the slope estimates are statistically significant on both imports and exports. In particular, the slope coefficient estimate on imports is positive but that on exports is negative. The estimates suggest that import-oriented companies are more likely to have positive exposures to the dollar index variation whereas export-oriented companies are more likely to have negative exposures to the dollar index variation. Putting it different, stocks of import-oriented companies tend to react positively to dollar appreciation, but stocks of export-oriented companies tend to react negatively to dollar appreciation.

Our results also make intuitive sense. For export-oriented companies, dollar appreciation makes their exports more costly for foreign consumers and hence reduces their sales. As traditional wisdom goes, domestic currency appreciation hurts exports. On the other hand, for import-oriented companies, dollar appreciation makes their imports less expensive and hence increases their profit margins. Our regression results reflect the different impacts of imports and exports on the currency exposure. The results also highlight the potential danger (or ineffectiveness) in relating currency exposures to total trades.

## 3.6. Linking Dollar Exposure to Expected Stock Returns

Import- and export-oriented companies have systematically different currency risk exposures, but do their different currency exposures lead to different expected excess returns, or risk premiums, on their stocks?

We estimate the risk premiums on different types of risk exposures following a procedure popularized by Fama and MacBeth (1973). At each month $t$, we regress cross-sectionally next month's excess returns on the industry portfolios against the time-$t$ rolling-window estimates on the risk exposures of these industries,

$$ER^i_{t+1} = \eta^0_t + \eta^{fx}_t \beta^{fx}_{it} + \eta^{mkt}_t \beta^{mkt}_{it} + \eta^{smb}_t \beta^{smb}_{it} + \eta^{hml}_t \beta^{hml}_{it} + e^i_t, \tag{3.3}$$

where $\eta^0_t$ denotes the intercept of time-$t$ cross-sectional regression and $\eta^k_t$ denotes the risk premium estimate for each unit of risk exposure on the $k$-th risk factor, with $k = fx, mkt, smb, hml$, respectively. All risk exposures are estimated based on ten-year rolling windows and updated annually in July of each year. The time-series averages of the slope estimates capture the average risk premiums charged by the stock market on each unit of risk exposure in the four risk sources.

Table 3.4 report the time-series averages of the regression estimates under "I. Without IM/EX," with Newey and West (1987) $t$-statistics on the averages reported in parentheses. The average slope estimates are negative on the currency risk exposure and positive on the other three risk exposures. Nevertheless, none of the slope averages are statistically significant.

In this estimation, all risk exposures ($\beta_{it}^{k}$) are estimated by regressing the industry portfolio excess returns on the four risk factors with a ten-year rolling window. One potential reason for the low statistical significance suggests that the rolling-window estimation generates noisy risk exposure estimates.

To reduce the noise in the dollar risk exposure estimates and enhance the identification of the currency risk premium, we make use of our findings from the previous section that the currency risk exposures are related to the imports and exports of the corresponding industries. Therefore, the imports and exports quantities in an industry also contain useful information about the currency risk exposure. To incorporate the information in imports and exports in identifying the currency risk exposure and risk premium, we propose an alternative estimation method based on the following specification,

$$ER_{t+1}^{i} = \eta_t^0 + \eta_t^{fx}\left(\beta_{it}^{fx} + \lambda_{IM}\ln\left(\frac{IM}{ME}\right)_{it} + \lambda_{EX}\ln\left(\frac{EX}{ME}\right)_{it}\right) + \eta_t^{mkt}\beta_{it}^{mkt} + \eta_t^{smb}\beta_{it}^{smb} + \eta_t^{hml}\beta_{it}^{hml} + e_t^i, \tag{3.4}$$

where we regard the currency exposure as an average of information from three sources, the original rolling window regression estimates based on stock returns $\beta_{it}^{fx}$, the imports, and the exports. As we have done earlier, we scale the imports and exports by the market capitalization of each industry and then take natural logarithms on the scaled quantities. For pure identification reasons, we normalize the weighting on $\beta_{it}^{fx}$ to unity, and hold the weighting coefficients on imports and exports ($\lambda_{IM}$ and $\lambda_{EX}$) to be constant over time. We estimate the system of equations based on an iterative procedures. Given initial guess on the two coefficients, we perform cross-sectional regressions each month to obtain $\eta_t^k$. Then, we estimate two coefficients by maximizing the likelihood of the observations, assuming that the regression errors are identical, independent, and normally distributed. The likelihood estimates on the two coefficients are 1.163 for $\lambda_{IM}$ and $-1.032$ for $\lambda_{EX}$. Both estimates are strongly significant at 1% confidence level. The signs of the estimates are also consistent with our cross-sectional regression results in the previous section, where we find that the dollar exposure is positive associated with imports but negatively related to exports.

Table 3.4 reports the average risk premiums from this approach under "II. with IM/EX." With the enhanced identification using information from imports and exports, the time-series average of the currency risk premium $\eta_t^{fx}$ now becomes negative and statistically significant, with a $t$-statistic of $-1.68$. Thus, we not only have linked the currency exposure to fundamental international trading quantities such as imports and exports, but also have exploited this linkage in enhancing the identification of the currency risk exposure and currency risk premium.

The negative risk premium estimate suggests that in aggregate, market participants view dollar appreciation as a bad thing for the economy. Thus, a positive exposure to dollar appreciation generates higher returns when the economy is "bad" in terms of the currency valuation. Investors are willing to receive a lower expected excess return to gain positive exposures to dollar appreciation so that they can hedge against the bad state of the economy.

Fama and French (1992) has popularized a simpler, more intuitive, and more executable approach in quantifying risk premiums in terms of risk portfolios. Applying the approach to our case for the currency risk premium, we form stock portfolios based on the rankings of industry currency risk exposures. Starting from July 1983, we first estimate currency risk exposure using a ten-year rolling window according to the two methods (with and without import/export information) delineated above. Then, we sort the industries by their currency risk exposure estimates into five groups based on the quintile breakpoints of the currency risk exposures. We compute the equal-weighted returns on quintile portfolios. The quintile portfolios of currency risk exposures are rebalanced annually in July of each year.

Table 3.5 reports time-series averages of the percentage excess returns for the quintile portfolios The row under “High-Low” reports the average return spreads between the top quintile (High) portfolio and the bottom quintile (Low) portfolio. The row under “FF-3 alpha” represents the intercept term from a regression of the return spread between the top and bottom quintile portfolios against the three Fama-French factors, i.e., market, size, and book to market. Thus, this intercept term captures the portion of the currency risk premium that cannot be explained by three risk factors.

Consistent with the results in Table 3.4, the average currency return spreads are negative, more so when we rank the portfolios based on the enhanced currency risk exposure estimates incorporating the information in imports and exports. Controlling for the three market risk factors does not alter the results much. The FF-3 alpha is estimated at -0.2587% without information from imports and exports, and at -0.3621% with the information from imports and exports. These estimates imply a risk premium from three to four percent per annum, a quite economically significant quantity.

## 3.7. Conclusion

Economic theory suggests that the magnitude and direction of a company's currency risk exposure depends crucially on its fundamental involvement in international trade. For US industries, we find that the stock performance of an import-oriented company moves positively with the performance of the dollar, but the stock performance of export-oriented company tends to move against the dollar. Based on this finding, we use the imports and exports information to enhance the identification of the currency risk exposure for different industries, and analyze how each industry's expected stock return varies with its currency risk exposure. We identify a strongly negative risk premium for bearing positive exposures to the dollar. On average, import-oriented companies generate lower stock returns.

Table 3.1
Summary statistics of monthly returns on the dollar index and market risk factors
Entries report the summary statistics of monthly returns on the dollar index ($R^{fx}$), excess monthly returns over Treasury bill rate on the dollar index ($ER^{fx}$), excess monthly returns on the market portfolio ($R^{mkt}$), returns on the size ($SML$) and book-to-market ($HML$) risk portfolios, and the Treasury bill rate ($R_f$). Data are monthly from February 1973 to December 2001. The mean and standard deviations (Std) are in annualized percentages, the minimum and maximum are in monthly percentages. We also report the skewness, excess kurtosis, and monthly autocorrelation for each time series.

| | $R^{fx}$ | $ER^{fx}$ | $ER^{mkt}$ | $SML$ | $HML$ | $R_f$ |
|---|---|---|---|---|---|---|
| Mean | 4.566 | -1.995 | 5.886 | 2.235 | 5.587 | 6.562 |
| Std | 4.456 | 4.400 | 16.327 | 11.812 | 11.229 | 0.764 |
| Minimum | -4.175 | -4.585 | -23.130 | -16.700 | -12.800 | 0.150 |
| Maximum | 4.243 | 3.367 | 16.050 | 22.180 | 13.800 | 1.350 |
| Skewness | -0.081 | -0.166 | -0.518 | 0.641 | 0.035 | 1.195 |
| Kurtosis | 0.607 | 0.679 | 2.215 | 6.919 | 2.238 | 1.657 |
| Autocorrelation | 0.347 | 0.333 | 0.039 | 0.014 | 0.114 | 0.928 |

Table 3.2
Summary statistics on the imports, exports, and stock returns
Entries report the summary statistics on the natural logarithm of imports (IM), exports (EX) and the ratio of imports and exports to the market capitalization of the corresponding industry (IM/ME, EX/ME). The last column reports the summary statistics of the monthly excess log returns on industry portfolios (ER). In the first panel, we take time-series averages on the quantities and report the cross-sectional summary statistics of the time-series averages. In the second panel, we take cross-sectional averages and report the time-series statistics of the cross-sectional averages. The trade quantities and the market capitalization are both in millions. For the industry portfolio excess returns, the mean, median and standard deviation (Std) are in annualized percentages, the maximum and minimum are in monthly percentages. The cross-sectional statistics are over 402 industry observations. The time-series statistics are over 30 annual observations for the trade data and 360 monthly observations for the industry portfolio excess returns.

| | IM | EX | ln(IM) | ln(EX) | ln(IM/ME) | ln(EX/ME) | ER |
|---|---|---|---|---|---|---|---|
| A. Cross-sectional statistics of time-series averages | | | | | | | |
| Mean | 884.991 | 688.685 | 4.953 | 4.767 | -0.714 | -0.912 | 6.831 |
| Median | 177.197 | 121.356 | 5.021 | 4.703 | -0.648 | -0.937 | 8.709 |
| Std | 3268.866 | 1782.610 | 1.869 | 1.853 | 2.237 | 1.878 | 5.245 |
| Minimum | 0.082 | 0.168 | -3.073 | -1.845 | -7.592 | -6.783 | -14.466 |
| Maximum | 51708.752 | 14992.312 | 10.683 | 9.592 | 4.331 | 4.530 | 5.158 |
| Skewness | 11.265 | 5.263 | -0.282 | 0.034 | -0.307 | -0.039 | -3.849 |
| Kurtosis | 160.865 | 32.199 | 0.987 | 0.067 | 0.155 | 0.323 | 34.441 |
| B. Time-series statistics of cross-sectional averages | | | | | | | |
| Mean | 1950.052 | 1427.413 | 5.895 | 5.748 | -0.942 | -1.087 | 8.044 |
| Median | 1975.805 | 1385.499 | 6.249 | 6.024 | -0.920 | -1.037 | 11.407 |
| Std | 1231.271 | 919.761 | 0.877 | 0.892 | 0.119 | 0.110 | 18.802 |
| Minimum | 329.303 | 312.689 | 4.299 | 4.329 | -1.205 | -1.271 | -28.957 |
| Maximum | 4280.166 | 3089.771 | 6.981 | 6.916 | -0.775 | -0.924 | 19.404 |
| Skewness | 0.229 | 0.346 | -0.678 | -0.391 | -0.778 | -0.331 | -0.705 |
| Kurtosis | -0.965 | -1.151 | -1.024 | -1.407 | -0.157 | -1.361 | 4.061 |
| C. Cross-sectional averages of time-series statistics | | | | | | | |
| Mean | 884.991 | 688.685 | 4.953 | 4.767 | -0.714 | -0.912 | 6.831 |
| Median | 836.546 | 631.468 | 4.971 | 4.756 | -0.697 | -0.915 | 0.655 |
| Std | 374.742 | 261.144 | 0.381 | 0.276 | 0.342 | 0.307 | 33.994 |
| Minimum | 411.694 | 391.299 | 4.394 | 4.383 | -1.201 | -1.332 | -29.192 |
| Maximum | 1557.425 | 1149.775 | 5.464 | 5.151 | -0.281 | -0.507 | 34.227 |
| Skewness | 0.373 | 0.104 | -0.037 | -0.169 | -0.108 | -0.132 | 0.235 |
| Kurtosis | -0.755 | -0.437 | -0.962 | -0.512 | -0.434 | -0.614 | 3.390 |

Table 3.3

Summary statistics on the risk exposure estimates

Entries report the summary statistics on the slope estimates and their statistics of the following time-series regression on each industry portfolio,

$$ER_t^i = \beta_{i0} + \beta_i^{fx} ER_t^{fx} + \beta_i^{mkt} ER_t^{mkt} + \beta_i^{smb} SMB_t + \beta_i^{hml} HML_t + e_t,$$

where $ER^i, ER^{fx}, ER^{mkt}$ denote the monthly excess returns on the $i$th industry portfolio, the dollar index, and the market portfolio, respectively, and $SMB$ and $HML$ are the size and book-to-market risk factors. All regressions are performed on monthly returns over the sample period from February 1973 to December 2001. The summary statistics are over 402 industries for the full-sample estimates and 375 for the rolling-window estimates. The last column reports the statistics on the R-squares of the regressions.

| | $\beta^{fx}$ | | $\beta^{mkt}$ | | $\beta^{smb}$ | | $\beta^{hml}$ | | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| | Estimates | $t$-stat | Estimates | $t$-stat | Estimates | $t$-stat | Estimates | $t$-stat | |
| A. Cross-sectional statistics of full-sample estimates | | | | | | | | | |
| Mean | 0.048 | 0.125 | 0.968 | 8.079 | 0.979 | 5.040 | 0.332 | 1.801 | 0.397 |
| Median | 0.043 | 0.098 | 0.977 | 7.498 | 0.955 | 4.576 | 0.360 | 1.748 | 0.394 |
| Std. Dev. | 0.629 | 1.009 | 0.280 | 4.555 | 0.546 | 3.342 | 0.484 | 2.317 | 0.161 |
| Minimum | -2.417 | -2.692 | -0.348 | -0.752 | -0.365 | -2.838 | -1.776 | -4.239 | 0.048 |
| Maximum | 1.799 | 3.134 | 2.057 | 23.391 | 3.311 | 18.795 | 2.516 | 9.668 | 0.878 |
| B. Cross-sectional statistics of time-series averages of rolling-window estimates | | | | | | | | | |
| Mean | 0.111 | 0.167 | 0.932 | 5.888 | 1.000 | 3.669 | 0.232 | 0.908 | 0.407 |
| Median | 0.047 | 0.097 | 0.940 | 5.712 | 0.997 | 3.426 | 0.246 | 0.947 | 0.412 |
| Std. Dev. | 0.614 | 0.896 | 0.264 | 2.856 | 0.543 | 2.175 | 0.437 | 1.266 | 0.160 |
| Minimum | -2.188 | -1.834 | -0.697 | -0.872 | -0.304 | -1.700 | -2.877 | -2.770 | 0.035 |
| Maximum | 2.994 | 3.306 | 1.980 | 16.930 | 3.496 | 13.575 | 2.215 | 4.519 | 0.884 |
| C. Time-series statistics of cross-sectional averages of rolling-window estimates | | | | | | | | | |
| Mean | 0.058 | 0.096 | 0.948 | 6.408 | 0.983 | 4.079 | 0.234 | 0.942 | 0.424 |
| Median | 0.054 | 0.083 | 0.949 | 6.550 | 1.023 | 4.065 | 0.229 | 0.958 | 0.429 |
| Std. Dev. | 0.061 | 0.107 | 0.027 | 0.787 | 0.120 | 0.294 | 0.128 | 0.563 | 0.055 |
| Minimum | -0.060 | -0.071 | 0.895 | 4.951 | 0.706 | 3.597 | 0.056 | 0.141 | 0.327 |
| Maximum | 0.164 | 0.302 | 1.009 | 7.621 | 1.163 | 4.617 | 0.577 | 2.287 | 0.501 |
| D. Cross-sectional averages of time-series statistics of rolling-window estimates | | | | | | | | | |
| Mean | 0.111 | 0.167 | 0.932 | 5.888 | 1.000 | 3.669 | 0.232 | 0.908 | 0.407 |
| Median | 0.110 | 0.169 | 0.929 | 5.863 | 0.998 | 3.612 | 0.210 | 0.813 | 0.402 |
| Std. Dev. | 0.296 | 0.496 | 0.142 | 1.111 | 0.246 | 0.927 | 0.259 | 0.912 | 0.074 |
| Minimum | -0.295 | -0.535 | 0.740 | 4.322 | 0.660 | 2.403 | -0.091 | -0.243 | 0.308 |
| Maximum | 0.529 | 0.875 | 1.126 | 7.450 | 1.330 | 5.042 | 0.606 | 2.257 | 0.512 |

Table 3.4

Identifying currency risk exposures and risk premiums

Entries report time-series averages and Newey and West (1987) $t$-statistics (in parentheses) of the coefficient estimates from the following cross-sectional regression performed at each month $t$,

$$ER^i_{t+1} = \eta^0_t + \eta^{fx}_t \beta^{fx}_{it} + \eta^{mkt}_t \beta^{mkt}_{it} + \eta^{smb}_t \beta^{smb}_{it} + \eta^{hml}_t \beta^{hml}_{it} + e^i_t,$$

where $ER^i_{t+1}$ denotes next month's excess return on the $i$-th industry portfolio, $\beta^k_t$ denotes the ten-year rolling-window risk exposure estimates, $\eta^k_t$ denotes the slope coefficient on each risk exposure, with $k = fx, mkt, smb, hml$ denoting the four sources of systematic risks in the stock market, and $\eta^0_t$ denotes the intercept of the regression. We consider two methods in estimating the currency risk exposure $\beta^{fx}_t$,

**I. Without IM/EX**: We regress excess returns on each industry portfolio to excess returns on the dollar index, the market portfolio, the size portfolio, and the book-to-market portfolio using a ten-year rolling window. The slope coefficients estimates represent the risk exposure estimates on the four risk sources, $\beta^{fx}_t$, $\beta^{mkt}_t$, $\beta^{smb}_t$, and $\beta^{hml}_t$.

**II. Without IM/EX**: We estimate the following system of equations,

$$ER^i_{t+1} = \eta^0_t + \eta^{fx}_t \left(\beta^{fx}_{it} + \lambda_{IM} \ln(IM/ME)_{it} + \lambda_{EX} \ln(EX/ME)_{it}\right)$$

$$+\eta^{mkt}_t \beta^{mkt}_{it} + \eta^{smb}_t \beta^{smb}_{it} + \eta^{hml}_t \beta^{hml}_{it} + e^i_t,$$

where the coefficients ($\lambda_{IM}$ and $\lambda_{EX}$) are hold constant over time. Given the two coefficients, the risk premiums are estimated using cross-sectional regression. The two coefficients are estimated by maximizing the likelihood of the observations, assuming that the regression errors are identically and independently normally distributed.

| Method | $\eta^0$ | $\eta^{fx}$ | $\eta^{mkt}$ | $\eta^{smb}$ | $\eta^{hml}$ |
|---|---|---|---|---|---|
| I. Without IM/EX | 0.4761 | -0.0129 | 0.1057 | 0.0864 | 0.0361 |
| | (1.12) | (-0.13) | (0.28) | (0.34) | (0.14) |
| II. With IM/EX | 0.4777 | -0.0655 | 0.124 | 0.0771 | 0.0181 |
| | (1.14) | (-1.68) | (0.34) | (0.30) | (0.07) |

Table 3.5

Average return spreads between high and low currency risk exposure portfolios

Entries report time-series averages of percentage monthly excess returns on quintile portfolios formed based on the rankings of currency risk exposures. The currency risk exposure is estimated in two alternative ways. The first approach (I. Without IM/EX) estimates the exposure by regressing the excess stock returns on the dollar index returns and other market risk factors, without incorporating information from imports and exports. The second approach (II. With IM/EX) incorporates the information in imports and exports in estimating the currency risk exposures. The row under "High-Low" reports return spreads between top and bottom quintile portfolios. The row under "FF-3 Alpha" is obtained from regressing the return spread on market, size, and book-to-market risk factors. We also report the Newey and West (1987) $t$-statistics for each estimate in parentheses.

| | I. Without IM/EX | | II. With IM/EX | |
|---|---|---|---|---|
| Low | 0.6438 | ( 1.63 ) | 0.7275 | ( 1.99 ) |
| 2 | 0.6870 | ( 2.00 ) | 0.7452 | ( 1.98 ) |
| 3 | 0.8175 | ( 2.18 ) | 0.8140 | ( 2.05 ) |
| 4 | 0.7441 | ( 1.86 ) | 0.6236 | ( 1.67 ) |
| High | 0.4510 | ( 1.22 ) | 0.4545 | ( 1.17 ) |
| High-Low | -0.1927 | ( -1.09 ) | -0.2730 | ( -1.29 ) |
| FF-3 Alpha | -0.2587 | ( -1.32 ) | -0.3621 | ( -1.61 ) |

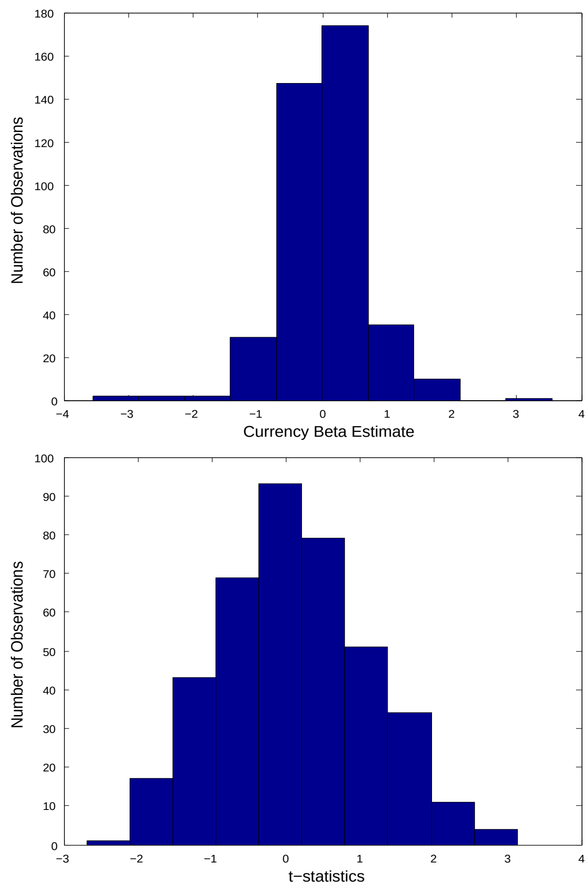


Fig. 3.1. **Histogram of slope coefficient estimates and $t$-statistics on currency exposures.** The left panel plots the histogram of industry currency risk exposures. The left panel plots the histograms of the corresponding $t$-statistics

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