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Inflation and Individual Equities

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Abstract

We study the inflation hedging ability of individual stocks. While the poor inflation hedging ability of the aggregate stock market has long been documented, there is considerable heterogeneity in how individual stock returns covary with inflation. Stocks with good inflation-hedging abilities since have had higher returns, on average, than stocks with low inflation betas and tend to be drawn from the Oil and Gas and Technology sectors. However, we show that there is substantial time variation of stock inflation betas. This makes it difficult to construct portfolios of stocks that are good inflation hedges out of sample. This is true for portfolios constructed on past inflation betas, sector portfolios, and portfolios constructed from high-paying dividend stocks.

1. Introduction

Inflation risk erodes purchasing power, redistributes wealth from lenders to borrowers, and threatens investors' long-term objectives which are often specified in real terms. The question of how stocks covary with inflation has been studied since Irving Fisher's seminal work in the 1930s and a large body of work has overwhelmingly documented that nominal stock market returns and inflation returns are negatively correlated.[1] This literature, however, has focused on how the behaviour of aggregate stock market indices covary with inflation. In this study, we focus on whether portfolios of individual stocks can adequately hedge inflation risk.

There are several important reasons to examine the inflation hedging ability of individual stocks as opposed to broad market indices. First, and most importantly, constructing portfolios based on individual stocks whose returns covary strongly with inflation has the potential to provide a much better inflation hedge than the aggregate market. An investor seeking to hedge inflation risk would optimally hold this firm-level constructed portfolio rather than a market-weighted index.

Second, there is considerable heterogeneity across firms. Different firms have different pricing power, which is the ability of a firm to set prices for new or existing goods, or to pass on price increases to consumers resulting from movements in input prices, such as commodities, labor costs, and interest rates. Although the overall stock market may be a poor inflation hedge, companies in certain sectors or with certain characteristics may have better inflation hedging properties than other companies. For example, Blanchard (1982) and Bils, Klenow and Kryvtsov (2003) find that prices of raw materials or goods early in the chain of production (for instance, gasoline and fresh food) are more flexible than those of processed goods or services. Gautier (2006) finds that energy prices have the greatest frequency of price changes among different components of price indices and Bresnahan (1989) finds a wide variety of market pricing power across industries.

Finally, examining individual stocks also allows us to investigate which types of stocks or sectors are better inflation hedges than others. Boudoukh, Richardson and Whitelaw (1994) show that some non-cyclical industries tend to covary positively, albeit not significantly, with inflation, whereas the contrary is true for cyclical industries. Sadorsky (2001) finds that, contrary to intuition, natural resource stocks (oil, gold, and other commodities) are not good

[1] See Fama (1981) for a classic early reference and more recently Erb, Harvey and Viskanata (1995) and Bekaert and Wang (2010).

inflation hedgers, even though industry practitioners often use allocations to this sector in particular to hedge against inflation (Ma and Ellis, 1989; Asikoglu and Ercan, 1992; MSCI Barra, 2008; Standard & Poor's, 2008). In addition to analyzing how different sectors hedge inflation risk, we also examine if good inflation hedges exhibit any value-growth, size, and momentum characteristic patterns which have been long documented to produce significant differences in average returns.

To measure the inflation hedging ability of individual stocks, we compute stock-level inflation betas following Bekaert and Wang (2010). We group stocks into portfolios ranking on inflation betas. This is done over the full sample, which allows us to conduct an ex-post analysis of which companies provided the strongest realized covariation between stock returns and inflation, and in a tradeable out-of-sample analysis, where the portfolios are constructed using information only available at the beginning of each month.

We find substantial variation in how individual stocks covary with inflation. While the correlation of the aggregate market with inflation is negative, there is a significant subset of stocks with high, and significantly positive, inflation betas over the sample. We rank stocks into quintile portfolios based on realized, ex-post inflation betas. The quintile portfolio with the highest ex-post inflation betas has overweights Oil and Gas and Technology stocks and has an inflation beta of 1.65. The Oil and Gas sector generally benefits from rising commodity prices while Technology firms often enjoy an advantage in setting or maintaining prices due to introducing new products. The remaining quintile portfolios have negative inflation betas. Thus, a non-negligible subset of stocks has covaried positively with inflation. Moreover, stocks that have been good inflation hedgers have had, on average, high nominal and real returns.

We find that the inflation betas exhibit pronounced time variation. As many as 20% of stocks, on average, exhibit sign changes in inflation betas from year to year. The large amount of time variation in inflation betas at the individual stock level makes it hard to construct portfolios of stocks that have good inflation hedging ability on an ex-ante basis. Moreover, the cross-sectional dispersion of inflation betas also varies through time. Most recently, the inflation betas for many stocks flipped sign during the financial crisis changing from positive before 2008 to negative over 2008-9. The instability of inflation betas extends to sector portfolios and portfolios comprising high dividend paying stocks.

By focusing on how inflation affects individual stock returns, our paper is related to a literature on cross-sectional asset pricing models which include inflation as a factor. An early reference is the factor model of Chen, Roll and Ross (1986) which includes unexpected shocks to inflation. This literature also includes papers which use interest rates or interest rate spreads as cross-sectional determinants of expected returns like Hahn and Lee (2006) as inflation and inflation risk account for a large part of the variation of interest rates and spreads (see Ang and Piazzesi, 2003). We place a special focus on the differences in average returns of stocks with inflation betas, while controlling for other systematic factor risk. This is not usually separately highlighted in the cross-sectional asset pricing literature.

2. Inflation-hedging measures

We use the beta of a stock return with respect to inflation as a measure of individual securities' inflation-hedging abilities. We construct portfolios sorted on inflation betas using both ex-ante and ex-post measures.

2.1. Inflation betas

Following Bekaert and Wang (2010) and others, our definition of inflation hedging is the how strongly a security's nominal return covaries with inflation in the following time-series regression:

$$R_{it} = \alpha + \beta\pi_t + \varepsilon_t, \tag{1}$$

where R_{it} is the monthly nominal return of a stock *i*, π_t the monthly rate of inflation, and ε_t the residual of the regression measuring the part of the nominal return that is not explained by inflation. We require at least 60 observations for each stock. Our results are almost unchanged if we augment equation (1) with the aggregate market and other systematic factors.

If β =1, we say that the stock is a perfect hedge against inflation. Note that a perfect inflation hedge does not imply that the correlation between the stock return and inflation is one due to idiosyncratic risk. The inflation beta allows investors to compute a hedge ratio; given a sufficiently diverse portfolio of stocks, the idiosyncratic risk disappears and only the systematic covariation between inflation and stock returns remains. This cannot be done for correlation measures, as correlation measures are not additive and do not take into account the magnitude of the stock's response to a given inflation movement. A negative inflation beta implies that a stock has poor returns when inflation is high.

There are other definitions of inflation-hedging capabilities in the literature.[2] Bodie (1976) defines the inflation-hedging capabilities of stocks by measuring how much the variance of real returns of a bond portfolio can be reduced using an equity portfolio. Fama and Schwert (1977), Schwert (1981), and Schotman and Schweitzer (2000) define an asset as a perfect hedge if it has a beta of one to expected inflation (or alternatively to both unexpected and expected inflation). Inflation hedging can also be defined in terms of covariance with a real rate (which can be instrumented by TIPS, but this is only possible after the late 1990s and TIPS embed a non-negligible liquidity component) or with conditional inflation (which is unobserved and must be specified through a time-series model). Our measure is direct and only involves the covariation with actual, observed inflation.

2.2. Data

Our sample of firms consists of all companies that have been constituents of the S&P500 over the sample period October 1989 to May 2010. For all common stocks present each month in the index, we obtain the monthly closing total return (cumulative stock price accounting for dividend gains and splits) and market capitalisation from Datastream (Thomson Reuters). We start in October 1989 as that is the date from which the dynamic composition of the S&P is available from Datastream.

We focus on the S&P universe as this is a typical universe for large institutional investors like pension funds and sovereign wealth funds, many of whom are concerned with inflation risk and consider the S&P universe investable. We also examine inflation and stock returns using the broader CRSP universe over 1962-2010, which contains 22,776 stocks, and find similar results. We allude to some of these results below, but concentrate on the S&P sample in this article. The full CRSP results are available in an internet appendix.

We use the U.S. consumer price index (headline CPI) from Datastream as the measure of inflation. We graph inflation over the sample in Figure 1. Inflation during the sample was moderate, averaging 2.7%, with a low volatility of 1.2%. The sample includes a peak of inflation of 6.3% during October and November 1990, after which inflation remained around 2-3%. Inflation again rises during 2007 reaching 5.6% in August 2008. Both of these events reflected rising commodity prices, especially for oil. There was also a period of negative

[2] We have also examined the ability of stocks to hedge expected inflation on the right-hand side of (1), similar to Kolluri and Wahab (2008), using median inflation forecasts from the Survey of Professional Forecasts. We find similar results across quantile portfolios using expected inflation, although there is a positive but insignificant relationship between S&P500 returns and expected inflation over 1989-2010, which confirms Kolluri and Wahab's findings.

inflation during the subprime mortgage crisis, with a trough of -2.1% in July 2009. We also use CPI data at the time of the release ("real time" CPI series), as provided by the Federal Reserve Bank of Saint Louis for the out-of-sample portfolio construction.[3]

2.3. Portfolio construction

To construct inflation hedging portfolios, we sort firms into quintile portfolios ranked on their inflation betas. We construct five portfolios (Quintiles 1 through 5, from the highest inflation beta to the lowest) weighted at each date by market capitalisations.[4] We construct a self-financed, dollar-neutral Q1-Q5 portfolio by buying the Q1 portfolio securities and shorting the Q5 portfolio securities. We record the returns of each portfolio as well as the portfolio inflation betas. We first construct in-sample portfolios, selecting the securities on the basis of betas calculated over the entire study period from October 1989 to May 2010 in Section 3.

We construct out-of-sample portfolios in Section 4. By using five-year rolling betas, we construct a dynamically rebalanced portfolio consisting of stocks selected on the basis of their past inflation betas, which is rebalanced monthly. The exercise is repeated every month for the October 1994-May 2010 period. Since the CPI series is not announced until the middle of the subsequent month, we omit the most recent month in the regressions. We also take "real time" CPI for the out-of-sample analysis.

After constructing quintile portfolios, we run monthly regression tests on the quintile portfolios sorted by inflation betas to check their Fama-French (1993) loadings and, following Carhart (1997), also include Jegadeesh and Titman (1993) momentum loadings:

$$R_{pt} = \alpha_p + \beta_p MKT_t + \gamma_p SMB_t + \delta_p HML_t + \eta_p MOM_t + \varepsilon_t, \tag{2}$$

where R_{pt} is the monthly excess-return of portfolio p over the risk-free rate. The three factors MKT_t SMB_t and HML_t constitute the usual Fama and French (1993) market, value and size factors, and MOM_t is the momentum factor. We refer to these factors as the FFC factors and obtain them from Kenneth French's website.[5] All returns are at a monthly frequency. We compute standard errors and t-statistics using the estimator in Newey and West (1987) with the number of lags equal to the recommendation in Newey and West (1994).

[3] See http://alfred.stlouisfed.org/

[4] Note that as a robustness check, we have also constructed equally weighted quintile portfolios, with very similar results not reported here.

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

3. Which stocks have hedged inflation best?

3.1. The best realized inflation hedging stocks

We first examine the in-sample behaviour of how stocks have covaried with inflation. By measuring inflation betas over the entire sample, this ex-post exercise reveals which stocks have provided the best inflation hedges over the period.

Table 1 lists the 20 stocks with the highest inflation betas in the S&P500, along with their sectors, annualized nominal and real return, abnormal return above FFC factors and inflation beta. For comparison, we include the coefficients for the S&P500. The top 20 inflation betas range between 15.63 for Enterasys Network (Technology) and 5.09 for Adobe Systems (Technology). In comparison, the S&P500 inflation beta is -0.52 and statistically insignificant. Thus, there are certainly stocks that have covaried strongly with inflation even though the typical stock and the aggregate market portfolio covary negatively with inflation. The best inflation-hedging stocks do not display particularly high abnormal returns above the FFC factors; only three stocks out of these 20 have a significant FFC alpha coefficient.

Within the top twenty inflation-hedging stocks, the best-represented sector (five of the top 20 stocks) is Basic Materials (companies engaged in the exploration or mining of metals, minerals and other commodities, development and processing of raw materials), followed by the Oil & Gas sector (four of the 20 stocks). Thus, almost half of the best inflation-hedging stocks are involved in commodity extraction or processing. The other sectors represented are Technology, Consumer Goods and Services and Healthcare, each represented by three companies. Note that two sectors are completely absent: Financials and Utilities.

3.2. In-Sample Portfolios

We sort stocks at time *t* based on the full-sample inflation beta and hold the portfolio from *t* to *t+1*. We reiterate that we are using forward-looking information of the covariation of inflation and stock returns over the whole sample, so our results have look-ahead bias and find the best realized inflation hedgers. Quintile 1 (Q1) stocks, the stocks with the higher inflation betas, have had the highest average performance while in quintile 5 (Q5), the stocks with the lowest inflation betas, stock returns tend to decrease when inflation is high.

Table 2 presents descriptive statistics on returns obtained for the five quintile portfolios, the self-financed Q1-Q5 portfolio, and the S&P500 over the entire sample. Real returns for the five portfolios are all positive, and monthly annualised real returns for the first three portfolios (quintiles 1 to 3) range between 6.34% and 7.36%, well above those of the last two portfolios (5.38% and 2.57%). Thus, stocks that have been good inflation hedgers have had, on average, high nominal and real returns. It is noteworthy that the last portfolio (Q5) and to a lesser extent the first portfolio (Q1) have more volatile performance than the middle ones (Q2-4): Q5 and Q1 have volatilities of 30.0% and 19.1%, respectively, compared with volatilities around 14-15% for the middle quintile portfolios. The Q5 portfolio also has much higher extreme risks, with kurtosis of 12.7 (compared to the portfolios Q1 to Q4 having a kurtosis between 3.8 and 4.5) reflecting distribution tails that are much fatter than normal. Equities with large negative inflation betas (and to a lesser extent those with large positive betas) thus appear much riskier than the others. The portfolios' success rates (percentage of months in which a portfolio's nominal return was higher than inflation) range from 58% to 63%, with an average of 62% for the S&P500.

Table 3 presents the results of the regression of monthly returns for each portfolio against inflation. The explanatory power of these regressions is very small, as shown by the very low R^2 and significant intercepts. By construction, Q1 portfolio has the highest inflation beta: 1.65 over the entire period, but this is not significant. All the other portfolios have negative betas, which range from -0.34 for Q2 to -2.22 for Q5, compared with the S&P500's inflation beta of -0.52. Thus, only a small subset of stocks has covaried positively with inflation and the average stock has been a poor inflation hedge. The long-short Q1-Q5 portfolio exhibits attractive inflation-hedging properties over the full sample, with a significantly positive inflation beta of 3.87. Not surprisingly, with the larger and longer CRSP sample starting in 1962, the Q1-Q5 inflation beta is even larger at 6.82 (not reported).

Table 4 breaks down the effects of exposure to the FFC factors for each portfolio. In Panel A, we report the S&P sample. There is some evidence that good inflation hedgers have higher returns than poor inflation hedgers, with a difference in alphas between Q5 and Q1 of 0.81% per month, and this is statistically significant. Q2 stocks have the highest 0.20% abnormal positive monthly return over the traditional factors and Q5, which contains stocks with the lowest inflation betas, has the lowest alpha, which is significantly negative at -0.72% per month. The most extreme quintiles Q1 and Q5 have higher market exposure than the others, with betas of respectively 1.1 and 1.5. Note that these quintiles also have higher total volatility (see Table 2). For the Q5 portfolio, the size effect is positive and significant, which means that stocks with negative inflation betas earn significant size premiums. This is consistent with smaller firms lacking the ability to raise their prices when the general inflation level rises compared with large firms; the best inflation hedgers have been the largest firms.

The coefficient of the HML factor is positive and significant for Q3-5 portfolios. The HML loading is particularly large for Q5 at 0.54. Thus, the best inflation hedgers tend to be growth stocks. The fact that the poorest inflation hedgers tend to be value stocks is consistent with the low prices of value stocks in some cases reflecting low market power and the reduced ability of the products of these firms to command premium prices. The momentum factor is insignificant both for the S&P500 and for most of the quintile portfolios (the only exception being Q1 with a significantly negative sign). It is striking that the Q5 portfolio, which contains the worst inflation hedgers, has the lowest performance, yet it is the only portfolio to earn both the size and value premiums. Its strong and significantly negative FFC alpha means that other systematic factors play a large role in explaining the differences of returns in stocks sorted by realized inflation-hedging properties.

We consider the larger CRSP universe from 1962 in Panel B of Table 4. Over the full sample, the best inflation hedgers have had almost identical risk-adjusted performance to the worst inflation hedgers with the difference between the Q1 and Q5 alphas being only 0.04% per month. There is one notable difference when very small stocks in the CRSP universe are included: the best inflation hedgers over the full sample have large, positive, and highly significant SMB coefficients. Thus, the best inflation hedgers have been the smallest stocks – which are excluded in the S&P500. The inclusion of these very smalls stocks does not improve out-of-sample performance (see the internet appendix).

3.3. Best in-sample inflation-hedging industries

We examine the sector composition of each of the quintile portfolios. Figure 2 compares the sector breakdown of the Q1 to Q5 portfolios (the percentages are calculated in terms of market capitalisation) to the S&P500. In Q1, the best inflation-hedging stocks have come from two types of industries: the Oil and Gas and Technology sectors are highly overrepresented (16.3% and 32.0%, respectively) relative to their weighting in the S&P500 (8.5% and 13.5%). Oil and Gas stocks tend to benefit from commodity price increases. This result is not surprising, given that episodes of inflation during the sample were largely related to major commodity price surges (the first episode, in late 1990, was linked to the Gulf War; the second, in the mid-2000s reflected the commodity price run-up amid speculation on very strong demand from emerging countries). The Technology sector contains companies which often create new, high value-added products that are differentiated from those already on the market, and can thus raise prices.

The worst inflation hedgers in Q5 include mainly Financial sector companies (34.6% of the quintile), in which it is very heavily overweighted relative to the S&P500 (15.3%). To a lesser extent, Q5 is also overweighted in Consumer Goods and Telecommunications. Financials' poor performance in inflationary periods has been documented in a number of studies which have shown that rising inflation reduces assets' real return and leads to increased demand for bank financing (see Boyd, Levine and Smith, 2001; Boyd and Champ, 2006). Most assets held by financial firms are nominal loans: as inflation increases the real value of these assets drops. The drop in real returns is associated with deteriorating average quality of borrowers and leads to credit rationing (Azariadis and Smith, 1996). The financial sector lends less, resource allocation is less efficient and intermediation activity decreases. Boyd and Champ (2006) also demonstrate a threshold effect, where banks' real net interest margins increase when inflation is moderate and decrease when inflation is high.

4. Can we predict inflation hedgers?

Given the strong in-sample relation between certain types of stocks and inflation, we now examine whether it would have been possible to pick good inflation-hedging stocks on an ex-ante basis.

4.1. Out-of-sample portfolio construction

We sort stocks based on the realized inflation betas over the last 60 months prior to time *t*.[6] We omit the current time *t* observation as inflation is not announced until the middle of the month and use "real time" inflation data. We hold this portfolio for one month from *t* to *t+1* and then rebalance monthly. Table 5 presents the performance of the out-of-sample portfolios. In contrast to the in-sample portfolios in Table 2, there is no evidence that stocks with high past inflation betas have, on average, higher real or nominal returns than stocks with low past inflation betas. In fact, each of the portfolios has a success rate around 60% (meaning that for 60% of the months in the study period, real returns were positive) and annualized real returns for the period as a whole are still positive, varying from 4.36% to 9.21%. In contrast to the preceding in-sample results, the risks of each of the five portfolios (Q1 to Q5) are nearly equivalent, with volatility ranging from 14.6% to 19.6%. Skewness and kurtosis do not

[6] Note that as a robustness check, we conducted the same analysis based on rolling inflation betas calculated on 36 and 84 months, with no significant difference in the results. We only present results based on 60-month betas.

significantly differ across the portfolios. The success rates for the larger post-1962 CRSP sample are even lower, ranging from 57% from Q1 to 53% to Q5 (see the internet appendix).

Table 6 reports the inflation betas on each portfolio from regression (1). The inflation beta of the Q1 portfolio is positive at 0.06, but much lower than that of the previously constructed in-sample portfolio (1.65), and not significant. Moreover, this portfolio has a beta lower than that of portfolio 5 (0.95), which is made up of the stocks with the lowest inflation betas. Clearly, stocks with high past covariation with inflation do not imply these stocks will have future high covariation with inflation.

In Table 7, exposure to the FFC factors reveals that the out-of-sample quintile portfolios have similar factor loadings for the market and SMB factors. Exposures to the value factor are positive and significant for the Q2-4 portfolios. Q4 and Q5 portfolio have positive significant exposure to the momentum factor. The difference in alphas between the Q1 and Q5 portfolios is 0.27% per month and is statistically insignificant. Note that although positive, the higher risk-adjusted alpha for Q1 is not due to this portfolio's ex-post inflation hedging ability, as Table 6 shows the inflation beta is only 0.06. For the post-1962 CRSP sample, the difference between the Q1 and Q5 FFC alphas is very similar at 0.33% per month and is also statistically insignificant (see the internet appendix).

Overall, Tables 5-7 are disappointing for finding good inflation hedging stocks on an ex-ante basis. While there is good inflation hedging ability for some stocks ex post, there is severe deterioration in ex-ante forecasting. The past covariation with inflation has little persistence and provides little predictive ability for a stock's future inflation hedging ability. We now further investigate the instability of these inflation loadings over time.

4.2. Inflation beta instability

Inflation betas on individual stocks vary substantially over time. They have low persistence, with high variability. Figure 3 shows the percentage of S&P500 stocks that flipped sign over one year during the October 1995 to May 2010 period. This graph illustrates the high inflation beta instability: on average during the whole sample period, 23.7% of the S&P500 stocks had inflation betas that changed sign over one year.[7] The recent period was particularly unstable. Whereas during the 1990s and early 2000s, an average of 22.1% of the stocks changed the sign of their inflation betas over one year (and the proportion was lower before the subprime

[7] Previous authors have documented that factor loadings for stock returns with respect to systematic factors vary over time (see for example, Ang and Chen, 2007; Lewellen and Nagel, 2006; Ang and Kristensen, 2010). The variation in inflation loadings is an order of magnitude larger than the variation in Fama-French loadings.

mortgage crisis), once the crisis broke, the proportion exploded to nearly 68% of the stocks. Indeed, this period coincided with a sharp rise in most stocks' inflation betas, which switched from negative to positive. This phenomenon is linked to the subprime crisis. During this period there was a simultaneous decrease in inflation (with monthly inflation rates of -0.9%, -1.8% and -0.7% from October to December 2008, respectively, which were the months with the largest monthly decline in inflation since 1950) and a decline in equity markets (returns of -8.9%, -16.8% and -7.2% for the S&P500 during the same months).[8]

Figure 4 shows the average rolling five-year inflation beta of the S&P500 stocks during 1994-2010. We see the high instability of the inflation beta, which alternated between periods when on average it was sharply negative (mid 1990s), others when it was near zero (late 1990s and early 2000s), and the recent period of the financial crisis when it turned positive. Another interesting observation is that the cross-sectional standard deviation of inflation betas also varies substantially over time. Figure 5 shows the beta distribution of S&P500 stocks at two selected dates within the study period, July 1999 and December 2008. Figure 5 clearly illustrates that inflation beta dispersion was much lower in 2008 than in 1999. Moreover, in 1999 the distribution was nearly symmetrical, but it became highly asymmetrical with a positive skew in 2008. The percentage of firms having an inflation beta greater than zero increased from 63% in July 1999 to 80% in December 2008.

Changing economic conditions, starting with the low macroeconomic volatility in the early 1980s (the "Great Moderation") and the changing nature of inflation shocks – from countercyclical to procyclical – have been stressed as the two main factors affecting the risk of stocks and its correlation with inflation in the US. The correlation changed from strongly negative in the late 1980s to mildly negative in the late 1990s (Li, 2002; Lettau, Ludvigson and Wachter, 2008; Brière and Signori, 2012). The same instability is observed in various countries: Bekaert and Wang (2010) demonstrate the unstable relationship between equity markets and inflation for a panel of some 50 countries. In addition to these macroeconomic factors, we note other sources of instability at the firm level related to firms' microeconomic characteristics. A company's pricing power may vary over time, reflecting such factors as its market positioning and competitive environment. Finally, the late 1990s saw a wave of mergers and acquisitions, which may also have contributed to changes in market power and

[8] This may be a regime switch. Inflation and inflation risk exhibit regime-switching behavior, as Evans and Lewis (1995) and Ang, Bekaert and Wei (2008) show.

the ability to raise prices (Kim and Singal, 1993; Prager and Hannan, 1998; Focarelli and Panetta, 2003).

4.3. Can we forecast time-varying inflation betas with stock characteristics?

Given the instability in the inflation betas, are there any variables that can help predict their variation? To answer this question we run monthly cross-sectional regressions of five-year rolling inflation betas on firm-specific characteristics, which include the book-to-market ratio, dividend yield, price-earnings ratio, and return volatility, which is computed using the past six months of daily returns prior to date *t*. We also include past return measures: momentum, which we define as the previous 12-month return of stock *i* at date *t*) and reversal, which is the return over the previous month. To test the hypothesis that the coefficient in the regression is zero, we follow the Fama and Macbeth (1973) and report the time-series average of the monthly cross-sectional coefficients, but our standard error accounts for possible heteroskeasticity and autocorrelation as we use Newey-West (1987) standard errors.

Table 8 reports the average cross-sectional coefficients, with t-statistics in parentheses, using stocks within each quintile and across the whole S&P500 universe. Not only do the inflation betas vary substantially over time, but this time variation is very difficult to forecast. In Table 8, there is not one firm characteristic that has a statistically significant coefficient.[9] The largest point estimates in magnitude are for the momentum characteristics: stocks with higher past returns tend to have lower inflation betas, but the relationship is insignificant.

5. Inflation hedging performance of sectors and high dividend stocks

We finally investigate how sectors and high dividend paying stocks hedge inflation risk. The preceding analysis suggests that the oil and gas and technology sectors are overrepresented in the first quintile of stocks, which have had the best inflation hedging performance over the full sample. Thus, sector-level portfolios may have good inflation hedging properties. Recently, it has been suggested that high dividend paying stocks may offer better inflation protection than other stocks.

5.1. Inflation hedging properties of S&P 500 sectors

We measure the inflation-hedging capacity of the ten S&P500 sectors. Table 9 presents the results of regression (1) of returns for each sector against inflation. All of the sector inflation

[9] All variables are also insignificant in univariate regressions (not reported).

betas were negative during the period, except for Basic Materials, whose beta was positive at 0.08 but not significantly different from zero. The Oil and Gas sector had the lowest inflation beta of -1.27, a surprising result in the light of the Section 3 findings that the best inflation hedges over the sample were overweight the Oil and Gas sector. Similarly, technology stocks were over-represented in the best ex-post inflation hedging firms, but the Technology sector has a negative inflation beta of -0.48 (not significant).

These aggregate results mask great variability over time and significant disparities among individual stocks. Figure 6 depicts sector inflation betas and their standard deviations over time. We graph the rolling five-year inflation beta averaged over all firms in that sector. Figure 6 shows that sectors, just like individual stocks, exhibit pronounced instability in inflation betas. For example, Financials—which over the whole sample have tended to be poor inflation hedges—have negative inflation betas only up to the late 1990s. During the financial crisis, the average financial inflation beta was positive; during this time Financials performed poorly and inflation was negative. Strong inflation beta variability is also noticeable for the Oil and Gas, Basic Materials, and Industrials sectors, with betas for all three sectors moving closely together (but with different amplitude) during the sample period. They moved from strongly negative in the mid 1990s to strongly positive (especially for Oil and Gas and Basic Materials) between 1999 and 2001.

Dispersion of inflation betas for stocks within sectors can also very high and varies substantially over time. As an example, Figure 7 presents the cross-sectional distribution of the Technology sector's inflation betas in July 1999 and December 2008. In this sector, which has historically experienced the highest average beta dispersion, 40% of the stocks had negative betas in July 1999. This individual dispersion was compressed very sharply in December 2008, where only 8% of the stocks had negative betas.

5.2. Inflation hedging properties of high dividend-paying stocks

It is often argued in the financial press that high dividend stocks have appealing inflation-hedging properties.[10] In this section, we compare the inflation hedging properties of our out-of-sample quintile portfolios with the S&P High Yield Dividend Aristocrats over its period of availability (since January 2000). This index, launched in November 2005, is designed to measure the performance of the highest dividend-yielding S&P Composite 1500 constituents

[10] See for example CNN Money (2010), "Stocks: Best moves to make now, by C. Fried, 19 May. Another example is Forbes Magazine (2010), "Dividend Stocks for Bond Investors", by Lehmann R., 6 December.

which have followed a managed dividend policy of consistently increasing dividends every year for at least 25 years.

Over January 2000 to May 2010, the High Dividend index generated exceptional performance compared with the S&P 500: an annualized real return of 6.16% versus -4.75% for the S&P500, with slightly lower volatility (15.8% versus 16.1%). But, the High Dividend index's inflation-hedging properties are disappointing. Its inflation beta was -0.45 compared with the S&P index's positive inflation beta of 0.47 (see Table 10). During this period the first quintile of stocks with the highest past inflation betas (out-of-sample) had an inflation beta of 0.08. The high returns on the highest dividend stocks are not because they are good inflation hedges. Rather, in a FFC regression (2), the High Dividend index has an especially low exposure to the market factor (market beta of 0.68), very significant exposure to value (HML loading of 0.71), and momentum (MOM loading of 0.23) factors. The FFC alpha of the High Dividend index is close to zero at 0.13% per month and insignificant. Thus, it is tradable systematic factor loadings, not inflation-hedging ability, which account for the high returns of high dividend stocks.

High-dividend paying stocks may be inflation hedges in the sense that their dividends comove highly with inflation, rather than their returns.[11] Table 11 shows that there is weak statistical evidence for this argument. We compute the average inflation beta over a longer sample, October 1989 to May 2010, of the price and dividend components of the 42 high dividend stocks in the S&P High Yield Dividend Aristocrats index in May 2010. Interestingly, while quarterly dividend growth shows a positive covariation with inflation (average inflation beta of 0.68, although it is insignificant), the opposite is true for the price return component (average inflation beta of -0.94, also insignificant). Both components tend to cancel each other, which explains why the total returns on high dividend stocks show no inflation hedging ability.

6. Conclusion

A large literature has documented the poor inflation hedging properties of the overall stock market. However, certain individual stocks have the ability to be good inflation hedges, even if the overall aggregate market has poor inflation hedging properties. Since the 1990s the top 20 stocks with the highest realized inflation betas have inflation betas exceeding five. If

[11] We thank a referee for suggesting this analysis.

stocks are ranked into quintile portfolios based on realized inflation betas over the sample period, the top quintile portfolio with the highest ex-post inflation betas has an inflation beta of 1.65 over the sample. This portfolio overweights Oil and Gas, which benefits from rising commodity prices, and Technology, a sector where the products of many firms command premium prices due to technological innovation. For comparison, the average beta of S&P500 stocks was -0.52 over the sample period. Thus, although a non-negligible subset of stocks has covaried positively with inflation, inflation betas are widely dispersed across individual stocks. Stocks with good inflation hedging properties have, on average, earned higher nominal and real returns than others.

However, trying to forecast ex-ante inflation betas at the individual stock level is not easy. Portfolios constructed on an ex-ante basis, where stocks are ranked on past inflation loadings, have little differences in next-month returns and exhibit little differences in inflation-hedging ability. The reason for the poor out-of-sample performance is due to the large time variation of inflation betas: approximately 20%, on average, of realized stock inflation betas change sign in the course of a year. The substantial variation of inflation betas makes it difficult to find stocks that are good ex-ante inflation hedges. Time-varying inflation betas make sector portfolios and indices holding only high dividend-paying stocks even worse inflation hedges than those constructed using firm-level information.

While we have used a simple and intuitive method to measure inflation hedging capabilities, by examining the covariance of a stock's return with inflation, there are other, more complicated measures. Another interesting extension might be to separate inflation into temporary and persistent components. We have also used CPI as the inflation measure. While the Billion Prices Project @ MIT has shown that CPI closely tracks a measure of inflation computed from hundreds of online retailers, an open question is whether another inflation measure – for example, a measure of inflation more closely tied to monetary aggregates, producer inputs, or some combination of many price series – is reflected in the cross section of stock returns.[12] Nevertheless, the inability to select firms that hedge CPI inflation on an ex-ante basis points to the need for investors to consider other asset classes as better inflation hedges.

[12] See http://bpp.mit.edu/usa/

References

Ang, Andrew, Geert Bekaert, and Min Wei. 2008. "The Term Structure of Real Rates and Expected Inflation." Journal of Finance, vol. 63, no. 2:797-849.

Ang, Andrew, and Joe Chen. 2007. "CAPM over the Long Run: 1926-2001." Journal of Empirical Finance, vol. 14, no. 1 (January):1-40.

Ang, Andrew, and Dennis Kristensen. 2011. "Testing Conditional Factor Models." forthcoming Journal of Financial Economics.

Ang, Andrew, and Monika Piazzesi. 2003. "A No-Arbitrage Vector Autoregression of Term-Structure Dynamics with Macroeconomic and Latent Variables." Journal of Monetary Econonomics. vol. 50, no. 3 (May):745-787.

Asikoglu, Yaman, and Metin R. Ercan. 1992. "Inflation Flow-Through and Stock Prices." Journal of Portfolio Management, vol. 18, no. 3:63-68.

Azariadis, Costas, and Bruce D. Smith. 1996. "Private Information, Money and Growth: Indeterminacy, Fluctuations and the Mundell-Tobin Effect." Journal of Economic Growth, vol. 1, no. 3 (September):309–332.

Bekaert, Geert, and Eric Engstrom. 2010. "Inflation and the Stock Market: Understanding the Fed Model." Journal of Monetary Economics, vol. 57, no. 3:278-294.

Bekaert, Geert, and Xiaozheng S. Wang. 2010. "Inflation Risk and the Inflation Risk Premium." Economic Policy, vol. 25 (October):755-806.

Bils, Mark, Peter J. Klenow, and Oleksiy Kryvtsov. 2003. "Sticky Prices and Monetary Policy Shocks." Federal Reserve of Minneapolis Quarterly Review, vol. 27, no. 1:2-9.

Blanchard, Olivier J. 1982. "Price Desynchronisation and Price Level Inertia." NBER Working Paper, 900.

Bodie, Zvi. 1976. "Common Stocks as a Hedge against Inflation." Journal of Finance, vol. 31, no. 2 (May):459-470.

Boudoukh, Jacob, Matthew Richardson, and Robert F. Whitelaw. 1994. "Industry Returns and the Fisher Effect." Journal of Finance, vol. 49, no. 5 (December):1595-1615.

Boyd, John H., and Bruce Champ. 2006. "Inflation, Banking, and Economic Growth." Federal Reserve Bank of Cleveland (May).

Boyd, John H., Ross Levine, and Bruce D. Smith. 2001. "The Impact of Inflation on Financial Sector Performance." Journal of Monetary Economics, vol. 47, no. 2 (April):221-248.

Bresnahan, Timothy. 1989. "Empirical Studies of Industries with Market Power." in Schmalensee R., Willig R. Eds., Handbook of Industrial Organization, vol. 2, North-Holland, Amsterdam.

Brière, Marie, and Ombretta Signori. 2012. “Inflation Hedging Portfolios: Economic Regimes Matter.” forthcoming The Journal of Portfolio Management.

Carhart, Mark M. 1997. “On Persistence in Mutual Fund Performance.” Journal of Finance, vol. 52, no. 1 (March):57-82.

Chen, Nai F., Richard Roll, and Stephen A. Ross. 1986. “Economic Forces and the Stock Market.” The Journal of Business, vol. 59, no. 3 (July):383-403.

Erb, Claude B., Campbell R. Harvey, and Tadas E. Viskanta. 1995. “Inflation and World Equity Selection.” Financial Analysts Journal, vol. 51, no. 6 (November-December):28-42.

Evans, Martin D. D., and Karen K. Lewis. 1995. “Do Expected Shifts in Inflation Affect Estimates of the Long-Run Fisher Relation?” Journal of Finance, vol. 50, no. 1(March):225-253.

Fama, Eugene F. 1981. “Stock Returns, Real Activity, Inflation and Money.” American Economic Review, vol. 71, no. 4 (September):545-565.

Fama, Eugene F., and Kenneth R. French. 1993. “Common Risk Factors in the Returns on Stocks and Bonds.” Journal of Financial Economics, vol. 33, no. 1 (February):3-56.

Fama, Eugene F., and James D. Macbeth. 1973. “Risk, Return and Equilibrium: Empirical Tests.” Journal of Political Economy, vol. 81, no. 3 (May-June):607-636.

Fama, Eugene F., and William G. Schwert. 1977. “Asset Returns and Inflation.” Journal of Financial Economics, vol. 5, no. 2 (November):115-146.

Focarelli, Dario, and Fabio Panetta. 2003. “Are Mergers Beneficial to Consumers? Evidence from the Market for Bank Deposits.” American Economic Review, vol. 93, no. 4:1152-1172.

Gautier, Erwan. 2006. “The Behaviour of Producer Prices: Some Evidence from the French PPI Micro Data.” ECB Working Paper, No. 699.

Hahn, Jaehoon, and Hangyon Lee. 2006. “Yield Spreads as Alternative Risk Factors for Size and Book-to-Market.” Journal of Financial and Quantitative Analysis, vol. 41, no. 2 (June):245-269.

Jegadeesh, Narasimhan, and Sheridan Titman. 1993. “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency.” Journal of Finance, vol. 48, no. 1 (March):65-91.

Kim, Han E., and Vijay Singal. 1993. “Mergers and Market Power: Evidence from the Airline Industry.” American Economic Review, vol. 83, no. 3 (June):549-569.

Kolluri, Bharat, and Mahmoud Wahab. 2008. "Stock returns and expected inflation: evidence from an asymmetric test specification." Review of Quantitative Finance and Accounting, Springer, vol. 30, no. 4 (May):371-395.

Lettau, Martin, Sydney C. Ludvigson, and Jessica A. Wachter. 2008. “The Declining Equity Premium: What Role Does Macroeconomic Risk Play?” Review of Financial Studies, vol. 21, no. 4 (July):1653-1687.

Lewellen, Jonathan, and Stefan Nagel. 2006. “The Conditional CAPM does not explain Asset-Pricing Anomalies.” Journal of financial Economics, vol. 82, no. 2 (November):289-314.

Li, Lingfeng. 2002. “Macroeconomic Factors and the Correlation of Stock and Bond Returns.” Yale ICF Working Paper, No. 02-46.

Ma, Christopher K., and M. E. Ellis. 1989. “Selecting Industries as Inflation Hedges.” Journal of Portfolio Management, vol. 15, no. 4:45-48.

MSCI Barra. 2008. “Hedging Inflation with Equities”, Research Bulletin (July).

Newey, Whitney K., and Kenneth D. West. 1987. “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.” Econometrica, vol. 55, no. 3 (May):703-708

Newey, Whitney K., and Kenneth D. West. 1994. “Automatic Lag Selection in Covariance Matrix Estimation.” Review of Economic Studies, vol. 61, no. 4 (October):631-653.

Prager, Robin A., and Timothy H. Hannan. 1998. “Do Substantial Horizontal Mergers Generate Significant Price Effects? Evidence from the Banking Industry.” Journal of Industrial Economics, vol. 56, no. 4 (December):433-452.

Sadorsky, Perry. 2001. “Risk Factors in Stock Returns of Canadian Oil and Gas Companies.” Energy Economics, vol. 23, no. 1 (January):17-28.

Schotman, Peter C., and Mark Schweitzer. 2000. “Horizon Sensitivity of the Inflation Hedge of Stocks.” Journal of Empirical Finance, vol. 7, no. 3-4 (November):301-315.

Schwert, William G. 1981. “The Adjustment of Stock Prices to Information about Inflation.” Journal of Finance, vol. 36, no. 1 (March):15–29.

Standard & Poor’s. 2008. “Inflation and Industry Returns: A Global Perspective”, September.

Tables and Figures

Table 1: Twenty best inflation hedging stocks from S&P500, regression of monthly returns on inflation, October 1989 – May 2010

Company Name	Sector	Ann. Mean	Ann. Mean real	α		$\beta_{inflation}$		Obs.
ENTERASYS NETWORKS	Technology	27.11%	24.61%	0.02	(0.96)	15.63	(1.22)	74
US SURGICAL	Healthcare	0.88%	-1.59%	-0.01	(-0.60)	12.81	(1.16)	74
SPRINT	Telecommunications	42.08%	39.57%	0.06***	(2.48)	8.72	(1.22)	64
TENET HEALTHCARE	Healthcare	10.89%	8.19%	0.00	(0.12)	8.43**	(1.68)	248
NATIONAL OILWELL VARCO	Oil & Gas	20.26%	17.90%	0.01	(1.17)	7.16***	(2.39)	62
HOMESTAKE MINING	Basic Materials	2.18%	-0.72%	0.00	(0.03)	6.95**	(1.71)	145
ASARCO	Basic Materials	6.74%	3.78%	-0.01	(-0.61)	6.52	(1.07)	120
PLACER DOME	Basic Materials	7.05%	4.13%	0.00	(-0.40)	6.44*	(1.45)	151
HARNISCHFEGER	Industrials	-1.06%	-4.01%	-0.01	(-0.87)	6.02	(0.59)	116
LIZ CLAIBORNE	Consumer Goods	2.11%	-0.67%	0.00	(-0.48)	5.83	(0.92)	230
MASSEY ENERGY	Basic Materials	4.52%	2.00%	-0.01	(-0.71)	5.72	(0.85)	157
BJ SERVICES	Oil & Gas	8.79%	6.34%	0.00	(0.09)	5.70***	(2.83)	94
MALLINCKRODT	Healthcare	16.65%	13.65%	0.00	(0.53)	5.50	(1.07)	132
MAXUS ENERGY	Oil & Gas	-1.68%	-5.16%	-0.02	(-1.11)	5.42	(1.02)	65
SEARS HOLDINGS	Consumer Services	2.59%	0.23%	0.00	(0.45)	5.23***	(2.42)	248
HALLIBURTON	Oil & Gas	14.40%	11.69%	-0.01	(-0.61)	5.23	(1.04)	62
JONES APPAREL GROUP	Consumer Goods	-22.54%	-25.11%	-0.02**	(-2.13)	5.19	(1.03)	85
JDS UNIPHASE	Technology	-20.17%	-22.63%	-0.01	(-0.87)	5.15	(1.20)	116
FREEPORT MCMOR COPPER & GOLD	Basic Materials	19.75%	17.33%	0.01	(0.47)	5.13*	(1.38)	178
ADOBE SYSTEMS	Technology	26.17%	23.78%	0.02**	(1.85)	5.09**	(1.83)	156
S&P500		8.82%	6.12%	0.00	(1.07)	-0.52	(-0.33)	248

****, **, * significant respectively at the 1%, 5% and 10% level*
α represents the constant of the FFC regression in equation (2)

Table 2: In-sample portfolios sorted by inflation hedging capabilities, S&P500 universe, monthly returns –descriptive statistics, October 1989 – May 2010

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	SP500
Ann. Mean	9.04%	10.06%	9.74%	8.09%	5.28%	3.76%	8.82%
Ann Mean real	6.34%	7.36%	7.03%	5.38%	2.57%	3.76%	6.12%
Median	1.07%	1.14%	1.09%	0.97%	1.17%	0.27%	1.28%
Max	13.99%	12.42%	13.36%	11.43%	52.04%	24.84%	11.44%
Min	-22.68%	-15.04%	-14.59%	-13.13%	-47.50%	-53.79%	-16.80%
Volatility	19.09%	14.11%	15.10%	14.32%	29.95%	20.95%	15.01%
Skewness	-0.53	-0.59	-0.49	-0.50	-0.25	-2.17	-0.66
Kurtosis	4.46	4.24	4.48	3.76	12.72	30.58	4.19
Success rate*	0.58	0.63	0.58	0.59	0.56	0.54	0.62
Obs.	248	248	248	248	248	248	248

**% on months when nominal returns are higher than inflation*

Table 3: In-sample portfolios sorted by inflation hedging capabilities, S&P500 universe, regression of monthly returns on inflation, October 1989 – May 2010

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	SP500
$\beta_{\text{inflation}}$	1.65	-0.34	-1.12	-2.48**	-2.22	3.87***	-0.52
	(0.86)	(-0.27)	(-0.73)	(-2.08)	(-0.55)	(3.45)	(-0.33)
R^2	0.01	0.00	0.01	0.04	0.01	0.05	0.00
Obs.	248	248	248	248	248	248	248

*T-statistics in parentheses. ***, **, * significant respectively at the 1%, 5% and 10% level*

Table 4: In-sample portfolios sorted by inflation hedging capabilities, regression of monthly returns on FFC factors

Panel A: S&P500 universe, October 1989 – May 2010

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	SP500
α	0.08%	0.20%**	0.09%	-0.02%	-0.73%***	0.81%***	0,00
	(0.51)	(2.34)	(0.98)	(-0.1)	(-2.7)	(2.77)	(1.07)
β_{MKT}	1.10***	0.90***	0.97***	0.91***	1.51***	0.41***	0.99***
	(21.64)	(47.92)	(28.77)	(22.68)	(15.67)	(-4.77)	(114.86)
β_{SMB}	-0.08	-0.23***	-0.21***	-0.27***	0.30***	-0.38***	-0.18***
	(-1.36)	(-8.73)	(-7.53)	(-9.27)	(2.89)	(-3.17)	(-13.04)
β_{HML}	-0.12**	-0,01	0.11***	0.09*	0.54***	-0.65***	0.04***
	(-2.15)	(-0.46)	(2.73)	(1.75)	(4.54)	(-5.90)	(3.82)
β_{MOM}	-0.15***	-0,03	0,01	0,04	0,01	-0.16*	-0.02*
	(-2.82)	(-1.28)	(0.31)	(1.12)	(0.11)	(-1.74)	(-1.68)
R^2	0,85	0,92	0,92	0,86	0,68	0,22	0,99
Obs.	248	248	248	248	248	248	248

*T-statistics in parentheses. ***, **, * significant respectively at the 1%, 5% and 10% level*

Panel B: CRSP stocks, January 1962 – May 2010

	Q1	Q2	Q3	Q4	Q5	Q1-Q5
α	-0.42%**	-0.18%***	-0.19%***	-0.25%***	-0.44%***	0.04%
	(-2.06)	(-2.41)	(-4.60)	(-3.34)	(-2.94)	(0.13)
β_{MKT}	1.17***	1.01***	0.92***	1.08***	1.25***	-0.08
	(15.76)	(47.59)	(53.48)	(54.23)	(19.05)	(-0.90)
β_{SMB}	0.53***	-0.05*	-0.13***	0.21***	0.65***	-0.09
	(3.94)	(-1.89)	(-5.85)	(6.47)	(6.12)	(-0.77)
β_{HML}	-0.13	-0.03	-0.01	0.11***	0.09	-0.22
	(-1.08)	(-0.74)	(-0.24)	(3.14)	(0.87)	(-1.52)
β_{MOM}	0.10	0.02	-0.01	-0.05**	0.01	0.10
	(1.08)	(0.74)	(-0.28)	(-1.98)	(0.17)	(1.00)
R^2	0.65	0.90	0,07	0.92	0.82	0.02
Obs.	581	581	581	581	581	581

*T-statistics in parentheses. ***, **, * significant respectively at the 1%, 5% and 10% level*

Table 5: Out-of-sample portfolios sorted by inflation hedging capabilities, S&P500 universe, monthly returns – descriptive statistics, November 1994 – May 2010

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	SP500
Ann. Mean	11.66%	7.51%	8.93%	6.80%	10.30%	1.36%	9.06%
Ann Mean real	9.21%	5.07%	6.49%	4.36%	7.86%	1.36%	6.34%
Median	1.35%	1.19%	1.32%	1.16%	1.62%	-0.06%	1.32%
Max	17.89%	12.09%	11.97%	10.04%	13.60%	16.13%	9.78%
Min	-22.63%	-14.40%	-17.24%	-20.06%	-17.92%	-25.11%	-16.80%
Volatility	19.64%	15.46%	15.45%	15.69%	17.19%	14.58%	15.66%
Skewness	-0.55	-0.59	-0.82	-1.10	-0.88	-0.56	-0.78
Kurtosis	5.07	3.88	4.63	5.33	4.85	10.11	4.17
Success rate*	0.61	0.59	0.64	0.59	0.61	0.49	0.62
Obs.	187	187	187	187	187	187	187

** % on months when nominal returns are higher than inflation*

Table 6: Out-of-sample portfolios sorted by inflation hedging capabilities, S&P500 universe, regression of monthly returns on inflation, November 1994 – May 2010

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	SP500
$\beta_{\text{inflation}}$	0.06	-0.52	0.12	0.90	0.95	-0.88	0.26
	(0.05)	(-0.47)	(0.13)	(0.98)	(0.95)	(-1.04)	(0.17)
R^2	0.00	0.00	0.00	0.00	0.00	0.02	0.00
Obs.	187	187	187	187	187	187	187

*T-statistics in parentheses. ***, **, * significant respectively at the 1%, 5% and 10% level*

Table 7: Out-of-sample portfolios sorted by inflation hedging capabilities, S&P500 universe, regression of monthly returns on FFC factors, November 1994 – May 2010

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	SP500
α	0.32%*	-0.07%	0.14%	-0.27%***	0.05%***	0.27%	0.02%
	(1.67)	(-0.57)	(1.26)	(-2.57)	(0.26)	(0.93)	(0.92)
β_{MKT}	1.05***	0.91***	0.84***	0.95***	1.03***	0.02	0.99%***
	(19.70)	(20.34)	(28.28)	(21.30)	(16.41)	(0.18)	(92.07)
β_{SMB}	-0.17***	-0.17***	-0.20***	-0.10**	-0.21***	0.04	-0.18***
	(-2.72)	(-2.86)	(-6.10)	(-2.08)	(-4.05)	(0.54)	(-11.39)
β_{HML}	-0,06	0.15***	0.17***	0.30***	0.09	-0.16	0.05***
	(-0.72)	(2.66)	(3.11)	(4.81)	(1.36)	(-1.18)	(3.88)
β_{MOM}	-0.15***	0.01	-0.09**	0.14***	0.15***	-0.31***	-0.01
	(-3.06)	(0.13)	(-2.21)	(3.47)	(2.99)	(-3.84)	(-0.96)
R^2	0.81	0.84	0.85	0.86	0.81	0.12	0.99
Obs.	187	187	187	187	187	187	187

*T-statistics in parentheses.***, **, * significant respectively at the 1%, 5% and 10% level*

Table 8: Cross-sectional regressions to predict inflation betas, October 1994 – May 2010

	Q1	Q2	Q3	Q4	Q5	S&P500
Book-to-market	-0.01	0.00	-0.00	-0.01	-0.05	-0.01
	(-0.22)	(0.06)	(-0.12)	(-0.23)	(-0.10)	(-0.26)
Dividend Yield	-0.16	0.06	0.05	-0.03	-0.78	-0.12
	(-0.29)	(0.21)	(0.27)	(-0.14)	(-0.59)	(-0.38)
P/E Ratio	-0.00	-0.00	0.00	0.00	0.00	0.00
	(-0.04)	(-0.07)	(0.22)	(0.20)	(0.19)	(0.25)
Return Reversal	-0.52	-0.70	0.22	0.29	0.48	-0.59
	(-0.03)	(-0.05)	(0.02)	(0.01)	(0.02)	(-0.03)
Momemtum	-0.48	-0.16	-0.37	-1.53	-6.48	-0.73
	(-0.11)	(-0.04)	(-0.10)	(-0.43)	(-1.18)	(-0.18)
Volatility	0.00	-0.02	-0.00	-0.02	-0.02	-0.01
	(0.03)	(-0.31)	(-0.10)	(-0.21)	(-0.13)	(-0.15)
Average R^2	0.23	0.18	0.20	0.22	0.23	0.12
Obs.	188	188	188	188	188	188

*Coefficients are average time-series cross-sectional regression coefficients. T-statistics in parentheses. ***, **, * significant respectively at the 1%, 5% and 10% level*

Table 9: S&P500 sectors, regression of monthly returns on inflation, October 1989 – May 2010

	Financials	Basic Materials	Industrials	Healthcare	Cons. Goods	Cons. Services	Utilities	Oil & Gas	Telecom	Techno
$\beta_{\text{inflation}}$	-0.50	0.08	-0.96	-1.01	-0.96	-0.51	-0.91	-1.27	-0.80	-0.48
	(-0.19)	(0.03)	(-0.54)	(-0.77)	(-0.94)	(-0.40)	(-0.72)	(-0.84)	(-0.80)	(-0.25)
R^2	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00
Obs.	248	248	248	248	248	248	248	248	248	248

*T-statistics in parentheses. ***, **, * significant respectively at the 1%, 5% and 10% level*

Table 10: Out-of-sample portfolios sorted by inflation hedging capabilities and S&P High Dividend, regression of monthly returns on inflation, January 2000 – May 2010

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	SP500	SP HYD
$\beta_{\text{inflation}}$	0.08	-0.54	0.09	1.19	1.32	-1.23	0,47	-0,45
	(0.07)	(-0.55)	(0.09)	(1.21)	(1.28)	(-1.30)	0,33	(-0.34)
R^2	0.00	0.00	0.01	0.01	0.01	0.01	0,00	0,00
Obs.	125	125	125	125	125	125	125	125

*. T-statistics in parentheses. ***, **, * significant respectively at the 1%, 5% and 10% level*

Table 11: High dividend stocks, regression of quarterly dividend growth and price returns on inflation, October 1989 – May 2010

	Dividend growth	Price return
α	2.74%	3.54%***
	(0.82)	(2.65)
$\beta_{\text{inflation}}$	0.68	-0.94
	(0.23)	(-0.65)
Average R^2	0.07	0.02
Obs.	248	248

*. T-statistics in parentheses. ***, **, * significant respectively at the 1%, 5% and 10% level*

Figure 1: US headline inflation (% yoy), October 1989 – May 2010

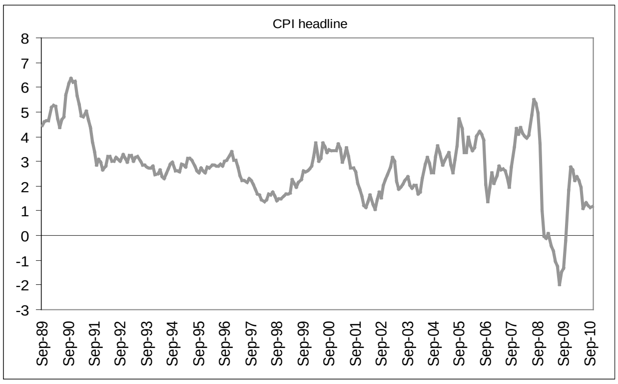


Figure 2: Market capitalization breakdown (month-end weights), in-sample portfolios repartitioned by sector vs S&P500, October 1989 – May 2010

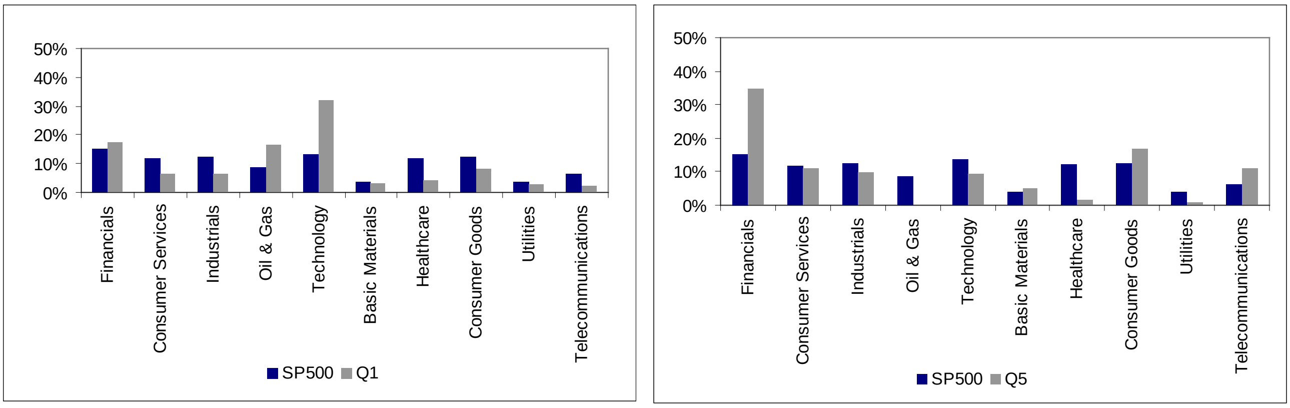


Figure 3: Percentage of changes in S&P500 stocks inflation beta over 1 year, October 1995 – May 2010

Figure 4: Average 5-year rolling inflation beta of S&P500 stocks, October 1994 May 2010

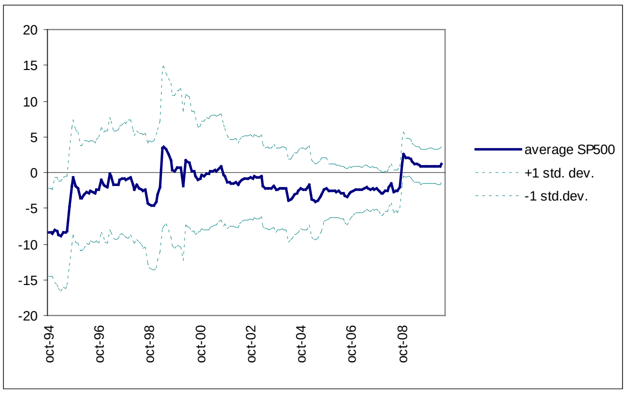
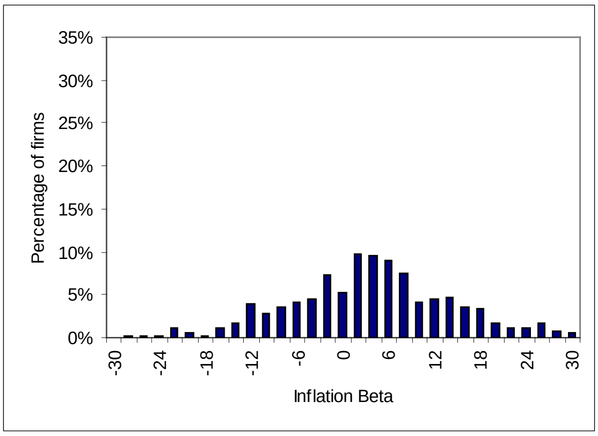


Figure 5: Cross-sectional distribution of inflation betas, S&P500, July 1999



December 2008

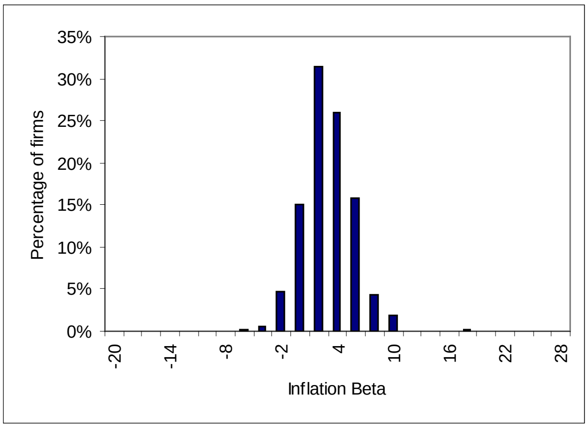


Figure 6: Average 5-year rolling inflation beta of S&P500 sectors, October 1994 – May 2010

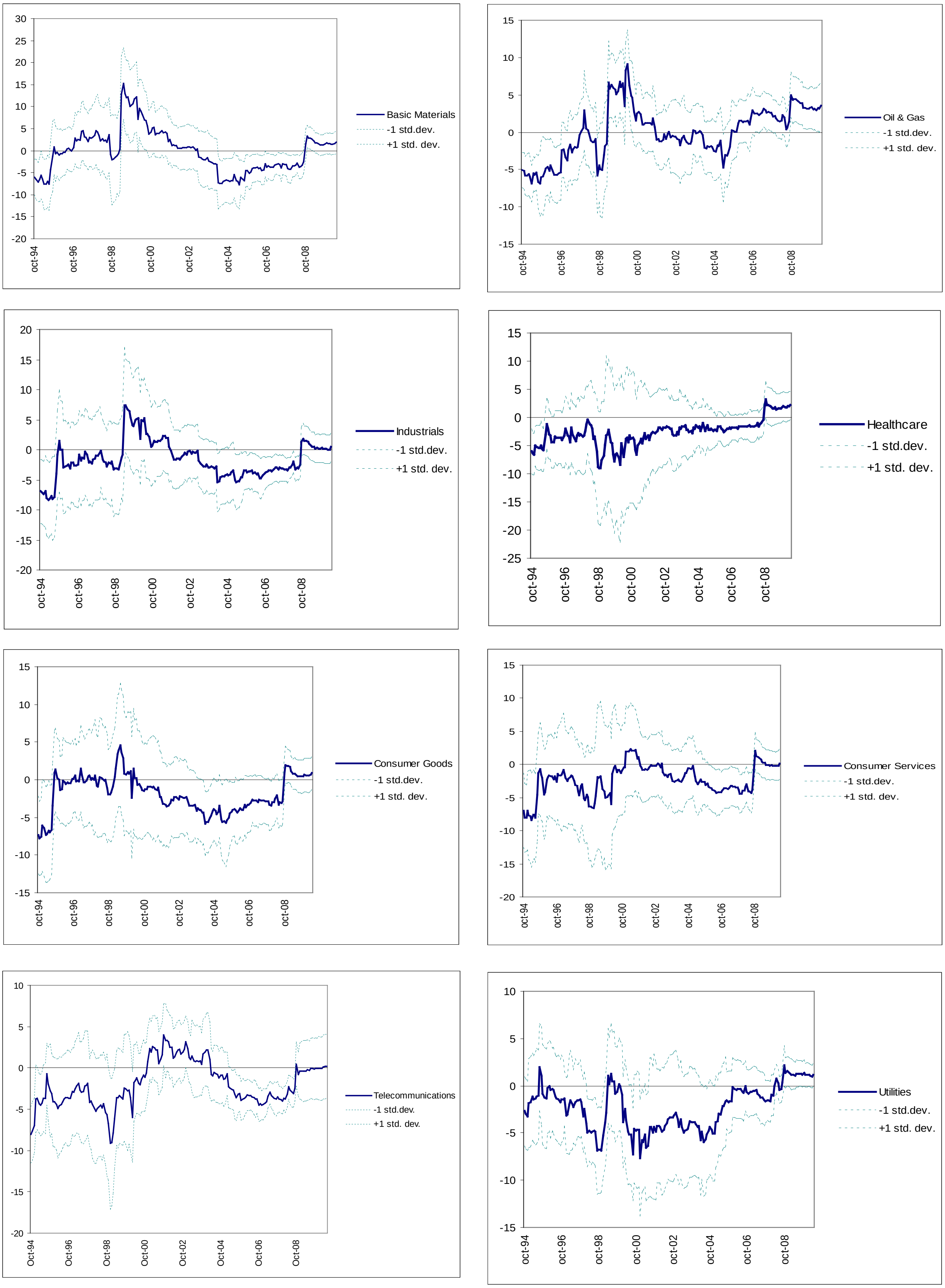
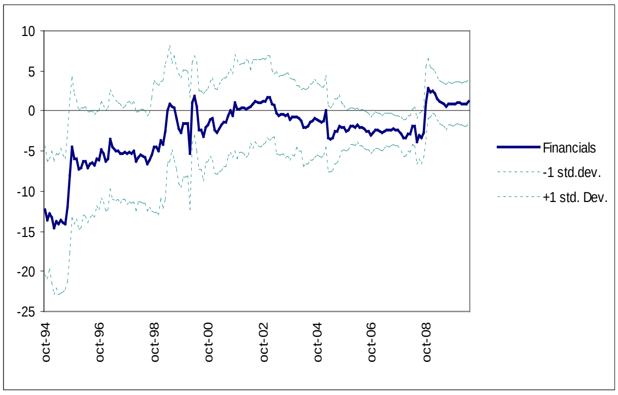


Figure 6 Continued



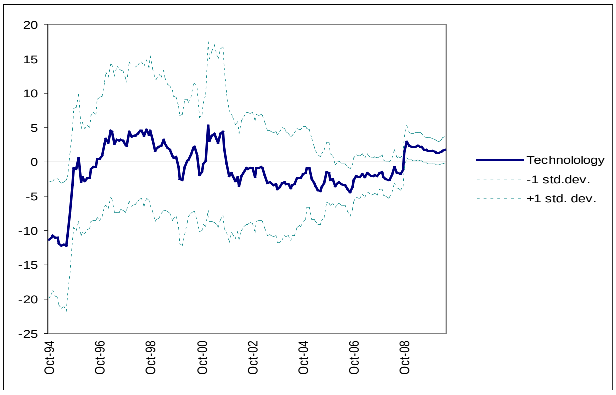
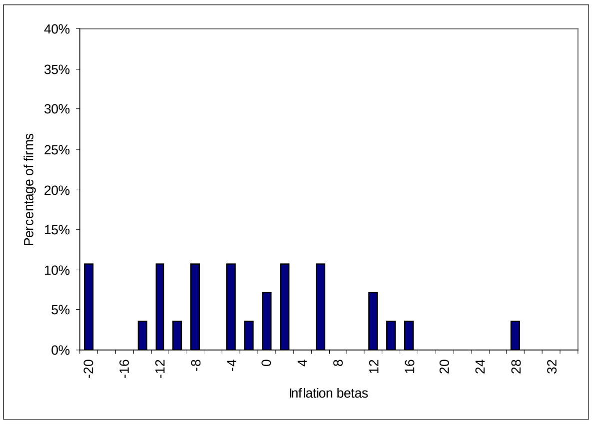
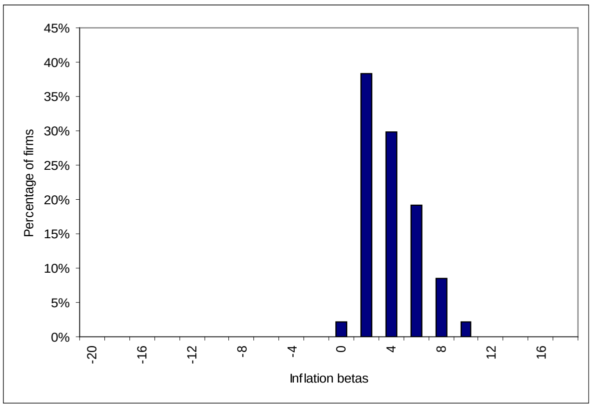


Figure 7: Cross-sectional distribution of inflation betas, Technology stocks,

July 1999



December 2008



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