Hedging Inflation with Individual US stocks: A long-run portfolio analysis

Georgios Bampinas[a], Theodore Panagiotidis [a,*]

[a]*Department of Economics, University of Macedonia, Greece*

Abstract

This paper examines whether individual stocks can act as inflation hedgers. We focus on longer investment horizons and construct in- and out-of-sample portfolios based on the long-run relationship (cointegration) of stock prices with respect to consumer prices. Empirical evidence suggests that investors are better off by holding a portfolio of stocks with higher long-run betas as part of asset selection and allocation strategy. Stocks that outperform inflation tend to be drawn from the Energy and Industrial sectors. Finally, we observe that the companies average inflation hedging ability declined steadily over the past ten years, while the number of firms that hedge inflation has decreased considerably after the recent downturn of the US economy.

Keywords: stock prices, good prices, hedging, generalized Fisher effect, quantile regression.

1. Introduction

Recent developments in the US economy, notably the rise in government deficits and debt levels, the increase in macroeconomic volatility, dollar weakness and the large volume of reserves being created by Fed, raised consumers and investors concerns of a potential inflation surge. Inflation erodes purchasing power of retirement savings, redistributes wealth from lenders to borrowers, and threatens private investors' long-term objectives which are often specified in real terms (see e.g., Bodie, 1989; Doepke

*Corresponding author.

Email addresses: bampinasg@uom.edu.gr (Georgios Bampinas), tpanag@uom.edu.gr (Theodore Panagiotidis)

and Schneider, 2006). The theoretical framework in this area is attributed to the seminal work of Irving Fisher (1930), who posited that the market interest rate comprises the expected real interest rate and expected inflation.[1] Conventional financial theory holds that equities should compensate for movements in inflation since they represent claims against real rather than nominal assets (Mishkin, 1992; Boudoukh et al., 1994). It is therefore of importance to examine whether inflation risk can be easily hedged in financial markets.

Different kinds of equities could offer contrasted inflation-hedging benefits. Blanchard (1982) examines the heterogeneity across sectors and finds that the variability of goods prices early in the chain production (food, energy) is larger than those of intermediate goods sector. In a similar vein, Clark (1999) argues that the response of producer prices to monetary shocks depends upon the manufacturing stage they belong to. Furthermore, there is a wide variation in the level of market pricing power across companies (Bresnahan, 1989). Fabiani et al. (2005) support that services firms change prices less often than others while retail firms do it more frequently. Gautier (2006) observes that the sectoral heterogeneity in the frequency of price change is quite similar in the euro area and in the US, with the prices of primary goods frequently modified. Accordingly, it is conceivable for investors to select stocks or sectors on the basis of their ability to hedge against inflation (hedging demand), as opposed to selecting them as a function of their outperformance potential (speculative demand).[2] Early on, Johnson et al. (1971) find that the individual stocks in the Dow-Jones Industrial Average were not consistent inflation hedges. Ang et al. (2012) examine the inflation hedging capabilities of S&P 500 stocks by utilizing the covariance of a stock's return with inflation. They postulate that only a small subset of stocks has covaried positively

[1] The Fisher Hypothesis about interest rates can be generalized to all assets in efficient markets (see e.g., Bodie, 1976 and Solnik, 1983 for stocks, Beckmann and Czudaj, 2013 for gold). Jaffe and Mandelker (1976, p. 450) term generalized Fisher effect, the hypothesis of independence between the expected real return in the stock market and the anticipated inflation rate. Arnold and Auer (2015) provide an up-to-date review of the literature on inflation hedging and the Fischer effect.

[2] A comprehensive discussion on this topic is provided by Amenc et al. (2011, p. 173).

with inflation and the average stock has been a poor inflation hedge in-sample as well as out-of-sample. Portfolios poor performance is mainly attributed to the substantial time variation of inflation betas.

In contrast to the Fisher hypothesis, many empirical studies document a negative relation between inflation and stock returns in the US (Nelson, 1976; Jaffe and Mandelker, 1976; Geske and Roll, 1983), with this phenomenon being universal rather than country-specific (Gultekin, 1983). Following attempts to resolve the puzzling negative short-run evidence the literature has since moved towards investigating the long-run hedging properties of stocks. A plausible explanation is that for investors with long term horizons, the question of inflation protection via stock investments is less about annual correlation and performance and more about the fundamental assurance that, over the long term, these investments earn returns that systematically exceed the inflation rate and, thus, protect purchasing power. In order to recover the long-run (*LR*) information, two alternative methodologies have been adopted: regressions of long holding-period stock returns on inflation using long span of data (Cagan, 1974; Lothian and McCarthy, 2001; Boudoukh and Richardson, 1993), and cointegration analysis of stock prices and consumer prices (Ely and Robinson, 1997; Anari and Kolari, 2001, 2010). Both proxies are shown to yield results more favourable to a positive long-run relationship between stock returns (prices) and inflation (consumer prices) with estimated coefficients broadly in line with the generalized Fisher effect (GFE, henceforth).

Our focus is on the inflation hedging properties of individual stocks from a long-run perspective. Within the GFE framework, we investigate the hedging ability of individual stocks that have shown significant cointegrating relationship with consumer price index. We construct in-sample and out-of-sample portfolios sorted on the long-run stock-level (individual) prices betas. In the first case, we conduct an *ex post* analysis of which companies and sectors provided the strongest realized comovement with consumer prices using the entire dataset. In the second case, for the *ex ante* analysis, we employ an estimation approach through which the estimated parameters of the model

used to test the stock prices/consumers prices relation are updated sequentially over time.[3] The latter is accomplished using rolling cointegrating regressions.

There are several reasons to examine the inflation hedging ability of individual stocks in a long-run framework. First, many institutional investors have long term horizons (Schotman and Schweitzer, 2000). In advanced economies where monetary policy focuses on price stability, investors and households may be most concerned about long-run inflation risk (household saving for retirement, liabilities of pension funds and endowments, etc.) and to a lesser extent about inflation movements in short horizons. Second, the vast majority of academic research has focused on how aggregate stock market indices covary with inflation. Even though the overall market may be a poor inflation hedge, companies from certain industry sectors and with specific characteristics may provide stronger long-run inflation hedging properties. Thus, constructing portfolios based on common stocks whose price comoves strongly with consumers prices has the potential to provide a much better inflation hedge than the aggregate market index. Third, equity hedging techniques based on correlation have substantial weaknesses inherent to the very nature of correlation as a measure of dependence such as lack of stability, short memory processes, applicable only to stationary variables, limit the use of long span data, loss of valuable information after de-trending level variables and sensitivity to the presence of outliers among others (Alexander and Dimitriu, 2004). Alexander (1999a) also argues that correlation reflects short-run comovements in returns, which are liable to great instabilities over time. On the other hand long-run comovements in prices, may occur even though periods when static correlation appear low. In this respect, hedging methodologies based on cointegrated assets may be more effective in the long term. Moreover, goods prices and stock prices are both known to be integrated processes with infinitely long memory, thus, estimating regressions in terms of their first (or higher) order differences implies

[3] Alexander and Dimitriu (2005) argue that the theoretical benefits of trading strategies based on cointegration relationships are more robust out-of-sample than the relationships that are identified on returns.

partial loss of valuable long-run information (Anari and Kolari, 2001).

Our results document how the magnitude of the inflation hedging ability varies across portfolios sorted on long-run betas. On the one hand, in-sample/*ex post* estimates of the stock prices/consumer prices model indicate substantial variation on how individual stocks comove with consumers prices in the long-run. While the long-run relation of the aggregate market with CPI is insignificant, there is a substantial subset of individual stocks with high, and significantly positive, consumers' price *LR* betas. Industrials and Energy sectors generally benefit from rising goods prices. We then sort stocks into quartile portfolios based on realized, *ex post* inflation betas (derived from the cointegrating regression). The portfolios consisting of stocks with the highest *ex post* long-run Fisher elasticities have inflation betas of 1.77 and 1.71 respectively, with the formers hedging ability to intensify on the left tail of the conditional distribution (lower returns). Moreover, stocks that have been good long-run inflation hedgers exhibit, on average, high nominal and real returns. On the other hand, out-of-sample/*ex ante* evidence reveals that the portfolio with 3 years rebalancing period exhibits the stronger hedging ability, with beta estimate of 1.12. The rest of the out-of-sample portfolios also exhibit positive inflation betas estimates ranging from 0.33 to 1.01. Both the in-sample portfolio with the higher betas and the out-of-sample portfolio with one to four years rebalancing period posit higher beta coefficients in magnitude and statistically significance, at the lower quantile of the conditional distribution. There is also evidence of considerable time variation in the values of individual firms *LR* betas and the amount of firms that show partial or full inflation hedging ability. Lower economic activity depresses companies long-run hedging ability. Further classification of stocks into sectoral portfolios shows that the Energy sector has the highest inflation beta, followed by the Materials and the Consumers Staples sectors. The sectoral inflation betas also exhibit pronounced time variation, with the Energy, Basic Materials and Industrials inflation betas moving closely during the sample period.

The remainder of this paper is organized as follows. The literature is reviewed in

Section 2. Section 3 discusses the data and the methodology as well as the procedure for in- and out-of sample portfolio construction. The empirical results are presented in Section 4 and the last one concludes.

2. Related literature

Research on the relationship between major asset classes and inflation is extensive (for a thorough and comprehensive review of the literature see Arnold and Auer, 2015). The relation between stock market returns and inflation remains an open issue. Early empirical studies focused on the US stock data provide voluminous evidence that common stocks are a poor hedge against both expected and unexpected inflation (see among others, Lintner, 1973; Oudet, 1973; Fama and Schwert, 1977). A range of competing hypotheses have emerged attempting to explain this negative short-term relationship: the "equity risk premium hypothesis" (Malkiel, 1979; Pindyck, 1984), the "tax effects hypothesis" (Feldstein, 1980; Summers, 1981), the "proxy hypothesis" (Fama, 1981; Bekaert and Engstrom, 2010), and the "inflation illusion hypothesis" (Modigliani and Cohn, 1979; Campbell and Vuolteenaho, 2004; Lee, 2010). Contrary to the US studies, Firth (1979) provides evidence in favor of a positive Fisher effect for UK over the period 1955 to 1976.

Some studies have examined the stock returns/inflation puzzle under different inflation regimes. Barnes et al. (1999) study the empirical relationship between inflation and a variety of asset returns of 25 countries for periods 1957 through 1996. They find that only in high inflation countries nominal returns provide some hedging properties against inflation. After examining several alternative hedging investments in the US, Attié and Roache (2009) conclude that of all the asset classes considered, equities are the least attractive hedge against inflation. Bekaert and Wang (2010) document higher inflation betas for emerging markets compared to developed markets. They point that the positive coefficient for emerging markets is mainly due to the Latin American countries which have experienced high inflation shocks. Knif et al. (2008) employ event

study methodology and conclude that stocks returns response to inflation is conditional on positive or negative inflation shocks in different states of the economy.

However, another branch of the literature argues that the Fisher hypothesis is an equilibrium hypothesis expected to hold in the long-run. Boudoukh and Richardson (1993) employ two century long time-series of annual stock and inflation returns for the US and UK, and strongly support a positive relation between nominal stock returns and inflation. Lothian and McCarthy (2001), using long span data for fourteen OECD countries over the post-World War II period and time series for the UK and the US over the longer period 1790 to 2000, conclude that equities constitute a good inflation hedge, but it takes "an exceedingly long time for this to happen." Ely and Robinson (1997) employ a multivariate model that incorporates real output and money in a cointegration framework. They examine the period 1957 to 1992, and do not find evidence that stock and goods prices are important components in the cointegrating vectors for the majority of the 16 countries considered. They conclude that in the long-run, stocks maintain their value relative to goods prices following both real and monetary shocks. One notable exception is the failure of stocks to maintain their value relative to goods prices driven by real output shocks in the US. Anari and Kolari (2001) also employ a cointegration approach with data from 6 industrialized countries. Over the period 1953 to 1998, the long-run generalized Fisher elasticity of stock prices with respect to consumer prices exceeds unity in four out of six cases ranging between 1.04 to 1.65. Alagidede and Panagiotidis (2010) investigate whether cointegration (parametric and nonparametric) exits between stock market and CPI for African countries. Nevertheless, none of the studies that employed cointegration has used common stocks to construct inflation hedging portfolios.

3. Data and methodology

3.1 Stock prices and stationarity tests

We use stock prices of companies that have been continuously constituents of the

S&P 500 Index for almost two decades, from January 1993 until August 2012. For all common stocks that are present in the index each month, we obtain the monthly closing prices (cumulative stock price accounting for dividend gains and splits) along with the market capitalization from Datastream (Thomson Reuters). The US Consumer Price Index (headline CPI) is downloaded from the Bureau of Labor Statistics. Following Ang et al. (2012), we also use CPI data at the time of the release ("real time" CPI series), provided by the Federal Reserve Bank of St Louis for the out-of-sample portfolio construction. For the CPI Series (headline and "real time") and all individual stocks, we have conducted four unit root and stationarity tests: (i) Dickey and Fuller (1979, (ii) Phillips and Perron (1988), (iii) the Ng-Perron (2001) and (iv) the KPSS. Our final sample consists of 345 individual stocks and the two CPI indices (all *I(1)*).[4]

3.2 Long-run and short-run regression analysis

Several studies have explored the issue of cointegration and asset prices.[5] The Engle-Granger (1987) (E-G, henceforth) method employed in many financial applications for cointegration testing is particularly appealing for several reasons. First, it is very straightforward to its implemention; secondly, the Johansen tests seek the linear combination which is most stationary whereas the E-G tests, being based on ordinary least squares, seek the linear combination having minimum variance. However, in risk management applications it is generally the E-G criterion of minimum variance, rather than the Johansen criterion of maximum stationarity, which is paramount; thirdly, there is often a natural choice of dependent variable in the cointegrating regressions (for example, in equity index arbitrage); and finally the E-G small sample bias is not going to be a problem since sample sizes are generally quite large in our case and the cointegrating vector is super consistent. [6]

[4]The unit root and stationarity tests results are available from the authors upon request.

[5]An extensive overview of this area is given in Alexander (1999b).

[6]See Alexander (1999a, p. 2043) for a discussion about the virtues of Engle-Granger methodology on financial applications.

In this paper, we consider a very simple concept of inflation hedging, namely, the long-run inflation beta. Our definition of long-run inflation hedging applies on how strongly a security's nominal price comoves with consumers' prices in the following time-series regression:

$$S_{it} = \alpha + \beta_1 CPI_t + \varepsilon_t \tag{1}$$

where S_{it} is the monthly log nominal price of a stock i, CPI_t the monthly log price level, and ε_t the error of the regression. We use the beta of a stock price with respect to consumer price index as a measure of individual securities' long-run inflation-hedging ability. Possible outcomes include $\beta_1 > 0$ partial *LR* hedge, $\beta_1 = 1$ one-to-one relationship, perfect *LR* hedge and $\beta_1 > 1$ stock performance superior. We construct portfolios sorted on long-run betas using both *ex ante* and *ex post* measures.

Next for the portfolios constructed on the basis of *LR* betas, we consider a simple concept of portfolios hedging ability (see eg., Ang et al., 2012; Bekaert and Wang, 2010), namely inflation beta, using the regression:

$$\Delta S_{pt} = a + \beta_2 \Delta CPI_t + e_t \tag{2}$$

Here, ΔS_{pt} is the portfolio monthly nominal return, ΔCPI_t is the monthly inflation rate and e_t is the part of the return not explained by inflation. Our measure of inflation hedging is straightforward and involves the portfolio returns covariation with actual inflation. Given that the variables are expressed in logarithms, β_2 coefficient is the short-run elasticity of portfolio returns with respect to inflation.

As noted earlier stock returns/inflation puzzle may be heterogeneous under different inflation regimes. Alagidede and Panagiotidis (2012) employ quantile regression and show a negative and significant relationship between S&P 500 returns and US inflation

throughout the conditional distribution. In a similar vein, we also employ the quantile regression approach proposed by Koenker and Bassett (1978) in an attempt to resolve the Fisher hypothesis in different levels of inflation and to gain a more complete picture of the stocks-inflation relationship across the spectrum.[7] More specifically, we measure their relation in different parts of the distribution instead of focusing on the average relationship. This approach, not only allows us to investigate whether or not the Fisher effect between stocks and inflation exists, but also provides a rigorous procedure to test in which quantiles the Fisher effect puzzle hold. In other words, it offers a novel way to study possible local validity of the Fisher hypothesis under different inflation regimes (low-medium-high).

3.3 Portfolio construction

We select stocks that have shown significant cointegration with consumer price index over the entire sample period. Equation (1) is estimated via Dynamic OLS (DOLS) for the stocks-CPI pairs that have shown significant cointegration at 10% level and the *LR* betas are saved. We sort stocks by their long-run betas to form quartile portfolios. Quartile 1 (Q1) is the portfolio with the highest betas, and Q4 is the portfolio with the lowest betas.[8]

We construct in-sample portfolios, selecting securities on the basis of betas calculated from January 1993 to August 2012. Along with four portfolios (Quartiles 1 through 4, sorted from the highest inflation beta to the lowest) weighted at each date by market capitalization, we have also constructed portfolio Q5 that contains all stocks which have shown superior performance against consumer price movements (*LR* beta above unity).[9] For the regression analysis, we employ a robust HAC (Newey-West) covari-

[7]For a more detailed analysis of quantile regression and the intuition behind it see Koenker and Hallock (2001).

[8]A negative inflation beta implies that a stock price moves to the opposite direction in the long-run when CPI is high. Therefore stocks with negative inflation beta were excluded from our analysis.

[9]Note that as a robustness check, we have also constructed equally weighted quartile portfolios, with very similar results not reported here but available from the authors upon request.

ance matrix estimator (Newey and West, 1987). The number of lags or leads in DOLS regression was selected according to the Schwarz criterion. We record the returns of each portfolio as well as the portfolio inflation betas.

Proceeding in out-of-sample analysis, we construct dynamically rebalanced portfolios on the basis of common stocks past cointegration ability (rolling E-G statistic) and long-run betas (rolling DOLS). The exercise is repeated for every rebalancing period (every 3, 6, 12, 24, 36, 48 and 60 months). Since the CPI series is not announced until the middle of the subsequent month, we omit the most recent month in the regressions and use the "real time" CPI.

Next, it would be interesting to examine whether the inflation-hedging portfolios returns can be adequately described by an asset pricing model. The three-factor model of Fama and French (1993) posits that expected returns can be explained by the excess market return, a firm size factor and a value factor. The factor mimicking portfolios are designed to have a unit exposure to the factor concerned and zero exposure to all other factors. Accordingly, after constructing the in- and out-of sample portfolios, we estimate the four factor model of Carhart (1997) which in addition to using the three factor loadings of Fama and French (1993) (FFC), also includes the momentum effect:

$$R_{pt} = a_p + \beta_p MKT_t + \gamma_p SMB_t + \delta_p HML_t + \eta_p MOM_t + \varepsilon_t \tag{3}$$

where R_{pt} is the monthly excess-return of portfolio p over the risk-free rate. We obtain from the French's online data library: monthly risk-free rates (on one month Treasury bills) and returns on risk factors which include MKT_t (market excess returns), SMB_t (small-minus-big firm returns), HML_t (high-minus-low book-to-market returns), and the MOM_t (winners-minus-losers returns).[10] All returns are at a monthly frequency. We compute standard errors and t-statistics using the Newey and West (1987) estimator

[10] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

with the number of lags equal to the recommendation in Newey and West (1994).[11]

4. Empirical results

4.1 The best long-run Inflation hedging Stocks

In this section, we examine the in-sample behavior of stocks that comove with goods prices. This *ex post* exercise reveals which stocks have provided the best long-run inflation hedges over the entire sample period. Table 1 lists the 25 stocks with the highest *LR* betas in the S&P500 universe (obtained from DOLS regression), along with their sectors, annualized return, the FFC alpha and the Engle and Granger *t*-statistic. The top 25 betas range between 10.27 for Gilead Sciences Inc (Health Care) to 5.21 for HCP Inc (Financials). For the S&P 500 index, insignificant long-run relationship with CPI has been detected. Thus, specific individual stocks comove with consumer prices in the long-run even though the aggregate market index has not shown significant long-run inflation hedging ability. The best inflation-hedging stocks do not display particularly high abnormal returns above the FFC factors; five stocks out of these 25 have a significant FFC alpha coefficient. Within the top twenty five inflation-hedging stocks, the best-represented sectors are Health Care, Energy, Industrials and Technology. Consumer Discretionary and Financials are represented by three companies. Other sectors represented include Basic Materials, Utilities and Consumer Staples.

A cross sector map of all the in-saple inflation hedging stocks is presented in Figure 1. The vertical axis denote the mean annualized return (in %) for each individual stock and the horizontal axis show the magnitude of the their *LR* beta coefficient estimates. Within the universe of inflation-hedging S&P500 stocks, the best-represented sector is Industrials (companies engaged in the manufacture and distribution of capital goods, transportation services and infrastructure, construction, engineering and build-

[11] We follow Newey and West's (1994) recommendation to set the number of lags equal to the highest integer less than $4 \times (T/100)^{(2/9)}$, where T is the number of periods in the sample. Applying this formula to our sample of $T = 236$ months results in a lag length of four months.

ing products, electrical equipment and industrial machinery), followed by the Energy sector (companies engaged in the exploration, production, marketing, refining and/or transportation of energy products and other consumable fuels). The other sectors that are strongly represented are Financials, Healthcare, Technology and Utilities. In Figure 1, we also observe that stocks associated with higher *LR* inflation betas also exhibit higher annualized returns.

4.2 In-Sample Portfolios

As noted, we chose individual stocks that have shown significant long-run relationship with consumers prices over the entire sample. Next, we sort stocks at time t on the basis of their full sample long-run betas and hold the portfolio from t to $t + 1$. Table 2 presents descriptive statistics on returns obtained for the four (quartile) portfolios, the portfolio Q5 and the S&P500 over the entire sample. Quartile 1 (Q1) stocks, the stocks with the higher *LR* betas, have had higher average performance than portfolios with lower *LR* betas (Q2, Q3, Q4). Q5 (the portfolio containing all stocks with inflation betas above unity) also exhibits positive annualized mean returns. Real returns for the quartile portfolios are all positive. Monthly annualized real returns for the first two portfolios (Q1 and Q2) are 9.06% and 8.84%, well above those of the last two portfolios (Q3 and Q4) which are 5.06% and 1.99%. Thus, stocks that have been good inflation hedgers in the long-run have had, on average, higher nominal and real returns. It is noteworthy that the first two portfolios have more volatile performance than the last ones: Q1 and Q2 have volatilities of 6.13% and 5.82%, respectively, compared with volatilities of 4.51% and 4.7% for the last two quartile portfolios. They also exhibit higher extreme risks, as it is observed from the negative skewness values. Kurtosis ranges between 4.59 and of 5.63, reflecting distribution tails that are fatter than normal. The portfolios' success rates vary between 48% and 61%, with an average of 59% for the S&P500.

Panel A in Table 3 presents the results of the regressions of monthly returns for each

value-weighted portfolio against inflation. The explanatory power of these regressions is very small, as shown by the very low R^2.[12] Q1 and Q2 portfolios have inflation betas of 1.77 and 1.71 respectively over the entire sample period, but these are not significant. The other portfolios have positive betas, which range from 0.44 for Q3 to 0.81 for Q4, along with the S&P500's inflation beta of 0.65. Thus, all the subsets of stocks have comoved positively with inflation and the average stock has been an adequate inflation hedge. The Q5 portfolio also exhibits inflation-hedging properties over the full sample, with a positive inflation beta of 1.33 but this is not significant.

We then proceed and employ quantile regression to relax the symmetry assumption (we employ three quantiles: $\tau = 0.25, 0.5, 0.75$, see Panel B in Table 3). In the first quantile a significant and positive relation is revealed for Q1 compared to an insignificant OLS coefficient, with an inflation beta of 3.34. The same holds for the S&P500 index with an inflation beta of 2.43. The latter could provide evidence in favor of GFE in cases when returns and inflation are relatively low (very low inflation could suggest low expectations, higher risk and as a compensation higher stock returns). Insignificant coefficients were found for the other two quantiles ($\tau = 0.5, 0.75$).

Table 4 breaks down the effects of exposure to the FFC factors for each portfolio. Q1 stocks have the highest 0.24% abnormal positive monthly return over the traditional factors and Q4, which contains stocks with the lowest long-run inflation betas, has the lowest alpha, which is significantly negative at -0.46% per month. Its' strong and significantly negative FFC alpha implies that other systematic factors play a considerable role in explaining the differences of returns in stocks sorted by realized long-run inflation-hedging properties. For the S&P500, the size effect is negative and significant. 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

[12] Any asset that reduces the risk of a liability (in the current context changes in the value of a liability caused by inflation) can be considered a hedging instrument even if it does not eliminate the risk completely (Brealey and Myers, 1991). This is done by taking a long position in an asset with returns that are found to be positively related to changes in the value of a liability. Therefore, in the present study the fact that the R^2 statistics obtained are considerably low should not be of primary importance.

been the largest firms. The coefficient of the HML factor is positive and significant for Q1 to Q5 portfolios and the S&P500 index. 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 for the S&P500 and all the in- sample portfolios.

4.3 Out-of-Sample Porfolios

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

We construct dynamically rebalanced portfolios consisting of stocks on the basis of the rolling window cointegration statistic and the DOLS betas, both estimated over the fixed-length 7 years (84 months) period preceding the rebalancing time.[13] 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 period and then rebalance every three months (Q$3m$), six months(Q$6m$), one year (Q$12m$), two years (Q$24m$), three years (Q$36m$), four years (Q$48m$) and five years (Q$60m$) .

The stock selection and allocation process is performed in a similar rolling framework. In each rebalancing we select the individual stocks that show significant long-run relationship with "real time" inflation (at 10% significance) level and pick up the stocks that provide partial or full hedge against consumer prices (positive long-run betas). Table 5 presents the performance of the out-of-sample portfolios in each rebalancing period. We compare the inflation hedging properties of out-of-sample portfolios, with

[13] As a robustness check, we conducted the same analysis based on rolling betas calculated on 60 and 108 months. While the results are similar between the 108 and 84 months analysis, the 60 months analysis slightly differs. This is may be attributed to the fact that 60 months period cannot be considered as an adequate time span in order to peform long-run analysis. The results are available from the authors upon request.

the S&P 500 index. All out-of-sample portfolios have on average higher nominal annualized returns than S&P 500 index. Each out-of-sample portfolio success rate ranges between 53% to 57%. The risks amongst the four portfolios are nearly equivalent, with volatility ranging from 4.13% to 4.66%. Kurtosis and skewness do not significantly differ across the portfolios.

Panel A in Table 6 reports the inflation betas on each portfolio from OLS regression. The inflation betas of all the out-of-sample portfolios are positive. Q*36m*, the portfolio with the three years rebalancing period has the higher covariation with inflation, with beta point estimate to 1.12. Panel B in Table 6 shows the results from quantile regression. Inflation beta coefficient in the 25th percentile is above unity for all out-of-sample portfolios except Q*6m*, ranging from 0.75 to 2.86. Still the Q*36m* portfolio exhibits the highest covariation with inflation, with a significant positive beta coefficient also found for Q*12m*, Q*24m*, Q*48m* and the S&P 500 Index. No significant relationship has been detected in neither of the other two quantiles (50th and 75th percentile), confirming previous evidence found in the in-sample analysis.

In Table 7, exposure to the FFC factors reveals that the out-of-sample portfolios have similar factor loadings for the market and SMB factors. Exposures to the value factor are positive and significant for all portfolios. The significant negative alpha in Q*12m* portfolios indicates that the differences in returns may be explained by other systematic factors.

4.4 Long-run Fisher elasticities and Firms hedging Instability

Figure 2 presents the proportion of S&P 500 stocks that have shown significant cointegration relationship with consumers' prices (left axis) and the average positive long-run betas (right axis) during the period January 2000 to July 2012. We observe that the number of individual stocks that have shown partial or full hedging ability against consumers prices vary substantially over time. Over the sample period, the amount of firms that have shown positive cointegration with consumers prices increased steadily

until the US recession. Specifically, during the early 2000s, 12 to 15% of the firms in our sample have shown positive cointegration relationship with consumers prices. Precendently the US recession, this proportion rose to nearly 40%. Indeed, shortly after the beginning of US business cycle contraction the number of firms that partially or fully hedge movements in consumers' prices followed a downward trend, which exacerbated after the Lehman Brothers collapse with a decline approximately to 30%. This period coincided with a slightly fall in most stocks' long-run inflation betas (right axis). Moreover, we observe a decline of the positive *LR* betas, which ranged from high value of eight (early 2000) to near five (in the mid-2000s) falling slightly to four (during recent recession period). Both phenomena are clearly linked to the subprime crisis, when there was a large decrease in US inflation from October to December 2008 and a simultaneous decline in equity markets during the same months. In response to the crisis, central banks injected liquidity into the system through quantitative easing policies.[14] These were initially successful in preventing larger declines in inflation (Martin and Milas, 2013). On the other hand, Blot et al. (2014) argue that for the US, over-borrowing may be one of the major channels through which inflation and financial instability are linked (via the booming economy and/or excessive liquidity provision). Nevertheless, subsequent quantitative easing policies have been less effective in driving inflation; to the extent that these uncoventional policies have not been a risk for inflation, as we move (roll) in time, we observe a lower average inflation hedging ability in terms of stocks. It seems therefore that for the US, the financial crisis and the subsequent recession aggravate the firms *LR* hedging ability.

Figure 3 illustrates the cross section beta distribution of S&P 500 stocks for two selected months within the study period, October 2000 and December 2008. We observe that the *LR* beta dispersion was much lower in 2008 than in 2000. Moreover, in 2000, the distribution was symmetrical, while in 2008, it became asymmetrical with a positive

[14] A thorough discussion on the changes of monetary policy instruments and policymaking institutions around the recent global financial crisis appears in Cukierman (2013).

skew. The proportion of companies with long-run inflation betas greater than zero remains high in both periods. This is in contrast with the result from the short-run betas in Ang et al. (2012) where the inflation beta dispersion differs substantially. Also the finding of positive long-run beta coefficient estimates in the vast majority of the S&P 500 companies, further reinforces the argument that the Fisher hypothesis is expected to hold in the long-run.

The cross-sector map of the two distinct periods discussed above is presented in Figure 4. On the vertical axis is reflected the market capitalization weight of each individual stock while on the horizontal axis the *LR* beta estimates. Financials and Information Technology are shown to be the two prevailing sectors, in terms of hedging ability (higher values of *LR* betas), in October 2000 followed by Industrials and Health Care sectors. After the outburst of financial crisis, the sectors that dominate are Energy and Utilities followed by Financials. This finding supports the argument that the composition of sectors that show *LR* inflation hedging properties also changes over time regarding the market conditions.

The fall in volatility of the aggregate economy occurring the last twenty years (Stock and Watson, 2002; Bernanke, 2004), and the changing nature of inflation shocks (Briere and Signori, 2012), have been two plausible explanations of the changing correlation between stocks and inflation in the US. Bekaert and Wang (2010) evident this unstable relationship in a panel of 50 countries. Ang et al. (2012) acknowledge companies related microeconomic characteristics (pricing power, market positioning, competitiveness) as a source of this instability. In addition to these factors, we observe that company's long-run hedging ability varies over time. Periods of low economic activity (recession) and high financial and macroeconomic volatility (subprime crisis) seem to contribute in the reduction of stocks average long-run hedging effectiveness.

4.5 Inflation hedging performance of sectors

We gauge the inflation-hedging capacity of the nine S&P500 sectors, focusing to common stocks that have shown long-run relationship with CPI. Table 8 presents the results of the regression of returns for each sectoral value-weighted portfolio against inflation.

According to the OLS regression (Table 8, Panel A), all of the sector inflation betas were positive during the sample period, except for Utilities, whose beta was negative at -1.02 but not significantly different from zero. Our results differ from Ang et al. (2012) who find negative inflation betas for all sectors (except basic materials) during the period October 1989-May 2010. The Energy sector had the highest inflation beta of 2.51. This is not a surprising result since the best inflation hedges over the sample were drawn from the Energy sector. The Materials and the Consumer Staples sectors have also high inflation betas above unity, but statistically significant only for the latter (at 10% level). While Industrial sector stocks were over-represented in the best *ex post* inflation hedging firms, the Industrial sector has a low inflation beta of 0.14 (not significant). Proceeding to the quantile regression analysis in Panel B, we observe a significant and positive Consumer Staple coefficient much higher than the OLS estimates in the 25th percentile. Negative and significant coefficients (at 10% level) were found for the Information Technology sector in the median (50th percentile) and higher (75th percentile) returns of the distribution. On the right tail of the distribution (higher returns), though we observe positive and significant coefficient for the Energy sector, much higher than the OLS coefficient.

These aggregate results mask great variability over time and significant disparities among individual stocks. In Figure 5 we observe that sectors portfolios exhibit pronounced instability in inflation betas over time. For example, Financials over the whole sample have tended to be poor inflation hedges except the early 2000s period. During the financial crisis, the average financial inflation beta was positive; this period of time Financials performed poorly and inflation was negative. Strong inflation beta variabil-

ity is also noticeable for the Energy, Basic Materials, and Industrials sectors, with betas for the two latter sectors moving closely together during the sample period. Average betas for Energy, Information Technology, Utilities and Health Care sectors moved from negative in early 2000s to positive, especially after the US recession period. All sectoral portfolios have positive inflation betas after the financial crisis period, even the Utilities sector with a negative *ex post* inflation beta.

5. Conclusions

Inflation erosion is one of the most important economic risks for consumers and investors alike. This paper examines the long-run relationship between individual stock prices and goods prices to determine whether stocks market investment can provide a hedge against inflation. The literature so far has focused on aggregate stock market indices and short-run measures. We use individual stocks from S&P500 over the sample period 1993 to 2012 and find that specific individual stocks have the ability to be good inflation hedges over the long-run. During the last 20 years, the top 25 stocks with the strongest comovement with goods prices have had *LR* beta values above five. Industrials and Energy are the best representing sectors according to the total amount of stocks that comove with consumer prices. No significant cointegration relationship between S&P500 and CPI has been detected over the sample period. Firms that have been good long-run inflation hedgers have had, on average, high nominal and real returns. We select stocks that have shown significant cointegration relationship with consumer prices and we sort them in a descending order according to their *LR* elasticity. The top portfolio, constructed on the basis of the highest ex-post long-run betas exhibits superior inflation hedging properties with a point inflation beta estimate of 1.77. Its inflation hedging ability is intensified in the left tail of the conditional distribution (lower returns) both in magnitude and in statistical significance.

We proceed by constructing dynamically rebalanced portfolios consisting of stocks

on the basis of the cointegration statistic and the *LR* (DOLS) betas. We find that the portfolio with three years rebalancing period has higher covariation with inflation, with beta estimates of 1.12. The remaining out-of-sample portfolios also exhibit positive inflation betas. These findings are further supported by quantile regression analysis. When returns are relative low (left tail of the conditional distribution) almost all out of sample portfolios hedge inflation with statistically significant beta coefficients for the portfolios with rebalancing periods one to four years.

Additionally, in- and out-of-sample portfolios seem to follow similar pattern according to their exposure to the FFC factors. The amount of firms that show positive *LR* relationship with CPI declines during the recent crisis period. Similar pattern is observed for the average *LR* hedging ability of firms during the last US recession period. The composition of companies that hedge movements in goods prices also changes over time along with the shape of firms *LR* beta distribution.

Further classification of individual stocks into sector-level portfolios reveals that Energy sector has the highest inflation beta, followed by the Materials and the Consumers Staples sectors. We find that the sectors inflation betas exhibit similar time variation, as we move throughout our sample. All sectoral portfolios display positive inflation betas after the recent financial crisis period.

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Table1: Twenty five best inflation long-run hedging stocks, regression of monthly prices on CPI, January 1993-August 2012

Company name	Sector	Ann. Mean	α		β_1		EG_{stat}
Gilead Sciences Inc	Health Care	20.31%	0.01	(1.31)	10.27***	(33.81)	-23.29
Express Scripts Holding Co.	Health Care	24.77%	0.01	(1.56)	10.03***	(49.69)	-47.92
Amphenol Corp A	Inf. Tech.	21.23%	0.01***	(2.12)	7.73***	(34.59)	-29.44
Fossil Inc	Cons. Disc.	23.07%	0.01	(1.1)	7.33***	(19.09)	-18.60
Public Storage	Financials	20.05%	0.01***	(2.69)	7.03***	(39.37)	-17.09
O'Reilly Automotive	Cons. Disc.	20.31%	0.01	(1.74)	6.86***	(32.97)	-23.96
Apache Corp	Energy	12.13%	0.00	(-0.27)	6.38***	(36.52)	-18.22
ONEOK Inc	Utilities	17.52%	0.00	(1.00)	6.28***	(32.74)	-21.96
Fastenal Co	Industrials	18.16%	0.01*	(1.61)	6.15***	(31.08)	-26.01
Roper Industries Inc	Industrials	18.52%	0.01*	(1.68)	6.01***	(38.03)	-27.85
Helmerich & Payne Inc	Energy	13.70%	0.00	(0.13)	5.95***	(31.9)	-24.37
Bard, C.R. Inc	Health Care	11.23%	0.00	(1.17)	5.94***	(36.56)	-20.08
Praxair Inc	Materials	14.99%	0.00	(1.17)	5.93***	(36.24)	-19.50
Cerner Corp	Health Care	15.39%	0.00	(0.48)	5.87***	(18.91)	-18.09
Altria Group Inc	Cons. Staples	14.20%	0.01	(1.35)	5.86***	(29.34)	-16.17
Johnson Controls Inc	Cons. Disc.	12.88%	0.00	(0.36)	5.85***	(29.21)	-19.08
Microchip Technology Inc	Inf. Techn.	24.35%	0.01*	(1.62)	5.68***	(13.87)	-25.01
General Dynamics	Industrials	18.23%	0.01	(1.32)	5.66***	(20.41)	-20.08
Noble Corp	Energy	14.78%	0.00	(0.06)	5.57***	(17.21)	-19.29
Intuit Inc	Inf. Tech.	16.47%	0.01	(0.91)	5.44***	(15.08)	-18.94
Health Care REIT Inc	Financials	12.83%	0.00	(1.21)	5.43***	(33.58)	-14.54
Devon Energy Corp	Energy	10.57%	0.00	(-0.60)	5.41***	(28.06)	-18.28
Harris Corp	Inf. Tech.	13.28%	0.00	(0.44)	5.37***	(24.81)	-16.79
Caterpillar Inc	Industrials	15.00%	0.00	(0.27)	5.35***	(23.35)	-15.99
HCP Inc	Financials	13.23%	0.00	(0.83)	5.21***	(34.34)	-18.04
S&P500		5.97%	-0.00	(-5.96)	-	-	-

***,**,* denote significance at the 1%, 5% and 10% level. α represents the constant of the FFC factor model. β_1 is the *LR* elasticity of stock prices with respect to goods prices (Equation 1) estimated via Dynamic OLS. Numbers in parentheses are the values of the *t*-statistic. EG_{stat} is the Engle and Granger t-statistic.

Table 2: Descriptive statistics of in sample portfolios.

	Q1	Q2	Q3	Q4	Q5	S&P500
Ann. Mean(%)	11.50	11.27	7.50	4.43	8.14	5.96
Ann.Mean real(%)	9.06	8.84	5.06	1.99	5.71	3.52
Median(%)	1.80	1.48	0.87	0.71	1.17	1.12
Max (%)	19.10	15.57	13.85	12.88	13.65	10.23
Min(%)	-26.56	-27.38	-18.77	-21.41	-21.74	-18.56
Std.Dev.(%)	6.13	5.82	4.51	4.70	4.64	4.45
Skewness	-0.88	-0.91	-0.42	-0.75	-0.75	-0.85
Kyrtosis	5.34	5.63	4.59	5.63	5.3	4.55
Success rate	0.58	0.53	0.50	0.48	0.61	0.59
#Obs	235	235	235	235	235	235

Quartile portfolios are formed from January 1993 to August 2012 by sorting common stocks on S&P 500 based on the long-run Fisher elasticity of each stock against CPI. The lowest (highest) quartile contains stocks with the lowest (highest) *LR* beta. Q5 portfolio contains all stocks with *LR* betas above unity. Success rate denotes the percentage of months when nominal returns are higher than inflation.

Table 3: In-sample portfolios sorted by long-run hedging capabilities, S&P500 universe, regression of monthly returns on inflation

	Percentiles	Q1	Q2	Q3	Q4	Q5	S&P500
Panel A: OLS regression							
β_2		1.77	1.71	0.44	0.81	1.33	0.65
		(1.09)	(0.84)	(0.3)	(0.37)	(0.76)	(0.34)
R^2		0.00	0.00	0.00	0.00	0.00	0.00
Panel B: Quantile regression							
β_2	25th	3.34***	-1.27	-0.61	0.006	0.06	2.43**
		(2.75)	(-0.51)	(-0.48)	(0.00)	(0.02)	(2.37)
Pseudo R^2		0.01	0.00	0.00	0.00	0.00	0.00
β_2	50th	1.04	0.41	1.01	-0.4	-0.3	-0.32
		(0.64)	(0.21)	(1.06)	(-0.26)	(-0.17)	(-0.24)
Pseudo R^2		0.00	0.00	0.00	0.00	0.00	0.00
β_2	75th	0.08	0.76	-0.37	-1.09	0.47	-2.55
		(0.05)	(0.40)	(-0.28)	(-0.82)	(0.35)	(-1.60)
Pseudo R^2		0.00	0.00	0.00	0.00	0.00	0.00

The coefficients reported in Panel A and B are for the following regression: $\Delta S_{pt} = a + \beta_2 \Delta CPI_t + e_t$ where ΔS_{pt} is the portfolios one month return and ΔCPI_t is the monthly inflation rate (Equation 2). ***,**,* denote significant at the 1%, 5% and 10% level. The sample period is from January 1993 through August 2012. Numbers in parentheses are the values of the t-statistic.

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

	Q1	Q2	Q3	Q4	Q5	S&P500
α(%)	0.24	-0.02	-0.16	-0.46***	-0.15	-0.23***
	(0.69)	(-0.09)	(-0.99)	(-3.18)	(-0.88)	(5.96)
MKT	0.71***	1.07***	0.85***	0.85***	0.88***	0.98***
	(9.75)	(17.72)	(17.84)	(18.97)	(19.86)	(83.90)
SMB	-0.02	-0.03	-0.13*	0.00	-0.05	-0.18***
	(-0.20)	(-0.32)	(-1.65)	(0.05)	(-0.67)	(-14.29)
HML	0.39**	0.48***	0.42***	0.63***	0.49***	0.02**
	(2.46)	(6.24)	(4.34)	(7.87)	(5.58)	(2.03)
MOM	-0.02	0.05	0.00	-0.05	-0.00	-0.01
	(-0.37)	(0.94)	(0.04)	(-0.90)	(-0.06)	(-0.94)
R^2	0.29	0.65	0.72	0.75	0.73	0.98

Quartile portfolios are formed from January 1993 to July 2012 by sorting common stocks on S&P 500 based on the long-run Fisher elasticity of each stock against CPI. The lowest (highest) quartile contains stocks with the lowest (highest) beta. Q5 portfolio contains all stocks with positive betas. The sample period is from January 1993 through July 2012. The alpha raw shows Fama–French–Cahart four-factor alphas. All returns are expressed in percent per month. Newey and West (1987) adjusted t-statistics are shown in parentheses .

Table 5. Descriptive statistics of out-of-sample portfolios.

	Q3*m*	Q6*m*	Q12*m*	Q24*m*	Q36*m*	Q48*m*	Q60*m*	S&P 500
Ann. Mean(%)	1.93	2.43	1.09	2.8	2.29	2.44	2.56	-0.5
Ann.Mean real(%)	-0.47	0.02	-1.32	0.39	-0.12	0.03	0.15	-2.92
Median(%)	0.59	0.78	0.78	0.95	0.82	0.98	0.67	0.71
Max (%)	10.43	9.37	9.81	11.22	7.53	12.28	9.88	10.23
Min(%)	-16.07	-17.73	-20.68	-20.68	-17.34	-20.68	-15.63	18.56
Std.Dev.(%)	4.13	4.29	4.55	4.45	4.08	4.66	4.3	4.7
Skewness	-0.78	-0.94	-1.09	-0.99	-0.96	-0.79	-0.82	-0.63
Kurtosis	4.57	4.69	5.36	5.78	4.71	5.04	4.77	3.95
Success rate	0.53	0.57	0.55	0.56	0.55	0.56	0.53	0.52
#Obs	151	151	151	151	151	151	151	151

Out-of-sample portfolios are formed every rebalancing period from January 2000 to July 2012 by selecting stocks that: 1) have shown cointegration with consumers' prices and 2) have positive long-run betas, both estimated over a rolling calibration period of 84 months. Success rate denotes the percentage of months when nominal returns are higher than inflation.

Table 6: Out-of-sample portfolios sorted by long-run hedging capabilities, regression of monthly returns on inflation

	Percentiles	Q3*m*	Q6*m*	Q12*m*	Q24*m*	Q36*m*	Q48*m*	Q60*m*	S&P 500
Panel A: OLS regression									
β_2		0.38	0.46	1.01	0.89	1.12	1.0	0.33	0.88
		(0.22)	(0.24)	(0.53)	(0.45)	(0.67)	(0.51)	(0.17)	(0.47)
R^2		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: Quantile regression									
β_2	25th	1.83	0.75	2.57**	2.77***	2.86***	2.48**	1.48	2.65**
		(1.59)	(0.25)	(2.57)	(2.66)	(2.74)	(2.01)	(0.73)	(2.42)
β_2	50th	-0.90	-1.01	-0.94	-0.41	-0.37	-0.45	-0.87	-0.04
		(-0.75)	(-0.82)	(-0.73)	(-0.30)	(-0.29)	(-0.3)	(-0.67)	(-0.02)
β_2	75th	-1.60	-0.63	-0.41	-0.65	-0.55	-0.43	-1.68	-0.73
		(-1.56)	(-0.56)	(-0.36)	(-0.53)	(0.5)	(-0.33)	(-1.40)	(-0.51)
Pseudo R^2		0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.01

The coefficients reported in Panel A and B are for the following regression: $\Delta S_{pt} = a + \beta_2 \Delta CPI_t + e_t$ where ΔS_{pt} is the portfolios one month return and ΔCPI_t is the monthly inflation rate (Equation 2). ***,**,* denote significant at the 1%, 5% and 10% level. The sample period is from January 2000 through July 2012. Numbers in parentheses are the values of the t-statistic.

Table 7: Out-of-sample portfolios, regression of monthly returns on FFC factor

	Q3*m*	Q6*m*	Q12*m*	Q24*m*	Q36*m*	Q48*m*	Q60*m*
α(%)	-0.19	-0.13	-0.27*	-0.01	-0.14	-0.17	-0.15
	(-1.29)	(-1.05)	(-1.79)	(-1.07)	(-1.03)	(-1.4)	(-0.98)
MKT	0.80***	0.84***	0.85***	0.84***	0.78***	0.91***	0.81**
	(17.3)	(15.8)	(15.03)	(14.53)	(15.93)	(16.36)	(14.66)
SMB	-0.09*	-0.10**	-0.06	-0.09	-0.14**	-0.12**	-0.12
	(-1.70)	(-1.99)	(-0.96)	(-1.45)	(-2.48)	(-2.2)	(-1.92)
HML	0.20***	0.18***	0.20***	0.28***	0.22***	0.26**	0.27***
	(4.33)	(3.74)	(3.01)	(5.22)	(3.77)	(5.15)	(4.04)
MOM	0.05	0.04	0.01	0.01	0.02	0.03	-0.00
	(1.39)	(1.02)	(0.23)	(0.27)	(0.71)	(1.02)	(-0.16)
R^2	0.82	0.83	0.80	0.83	0.81	0.85	0.84

Out-of-sample portfolios are formed every rebalancing period from January 2000 to July 2012 by selecting stocks that: 1) have shown cointegration with consumers' prices and 2) have positive long-run betas, both estimated over a rolling calibration period of 84 months. The FFC alpha raw shows Fama–French–Cahart four-factor alphas. All returns are expressed in percent per month. Newey and West (1987) adjusted *t*-statistics are shown in parentheses

Table 8: S&P500 sector level value-weighted portfolios, regression of monthly returns on inflation, February 1993-August 2012

		Energy	Inf.Tech.	Materials	Indust.	Utilities	Heal.Care	Cons.St.	Cons.Disc.	Financials
Panel A: OLS regression										
β_2		2.51	0.41	1.74	0.14	-1.02	0.84	2.5*	0.37	0.21
		(1.21)	(0.13)	(0.55)	(0.06)	(-0.94)	(0.78)	(1.65)	(0.11)	(0.10)
R^2		0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Panel B: Quantile regression										
β_2	25th	1.53	2.21	0.88	-0.14	-1.77*	0.61	4.24***	0.84	0.12
		(0.68)	(0.67)	(0.39)	(-0.09)	(-1.89)	(0.40)	(3.01)	(0.48)	(0.03)
β_2	50th	2.2	-4.03*	-1.89	-1.04	-0.52	2.14	2.43*	-3.31	-0.69
		(1.42)	(-1.66)	(-0.91)	(-0.46)	(-0.52)	(1.53)	(1.72)	(-1.13)	(-0.40)
β_2	75th	4.12**	-4.83*	1.58	-1.83	0.42	1.56	0.7	-3.17	-0.46
		(2.5)	(-1.84)	(0.49)	(-1.09)	(0.52)	(0.76)	(0.49)	(-1.63)	(-0.36)
Pseudo R^2		0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00

Sectoral portfolios are formed from January 1993 to August 2012 by grouping common stocks that have shown positive long-run relation with CPI, according to the sector they belong. The coefficients reported in Panel A and B are for the following regression: $\Delta Sp_t = a + \Delta CPI_t + e_t$ where ΔSp_t is the portfolios one month return and ΔCPI_t is the monthly inflation rate (Equation 2). ***,**,* denote significant at the 1%, 5% and 10% level. Numbers in parentheses are the values of the *t*-statistic.

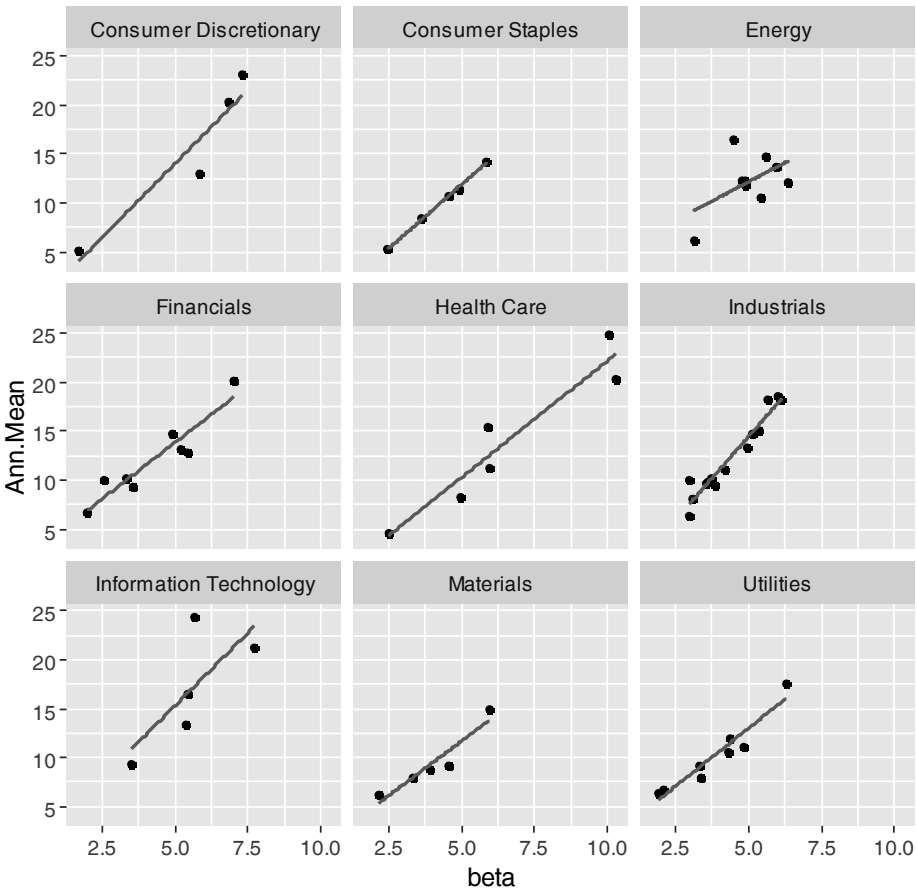


Fig. 1. Cross-sector map of the best long-run inflation hedging individual stocks. Blue line denotes the linear regression line.

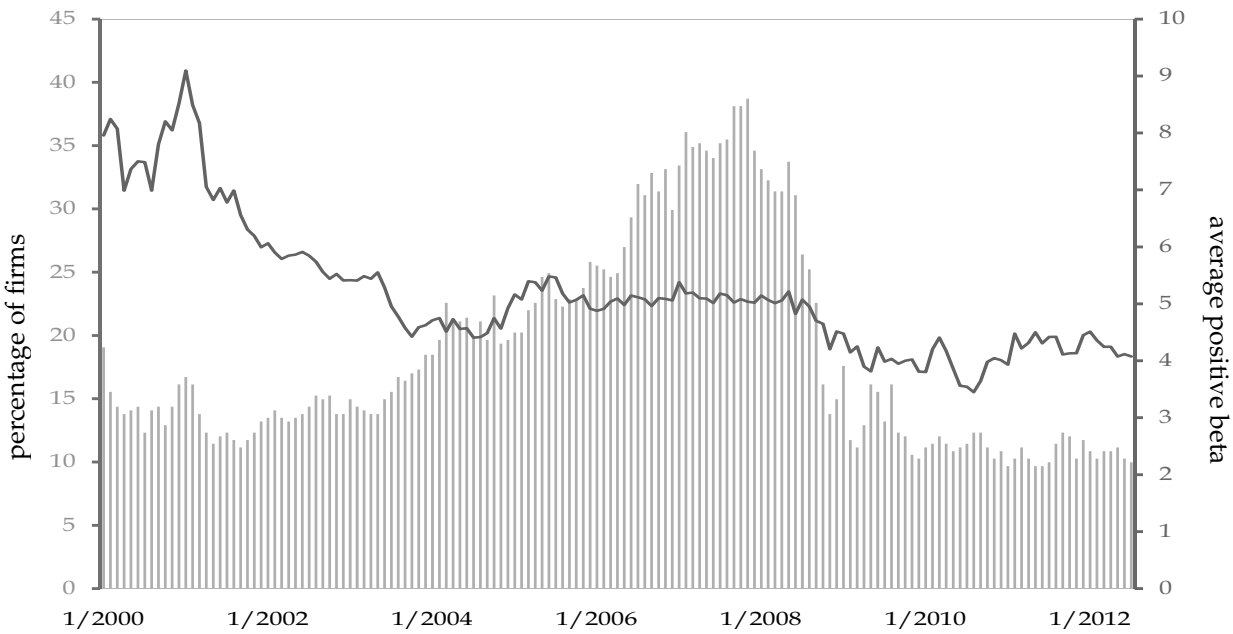
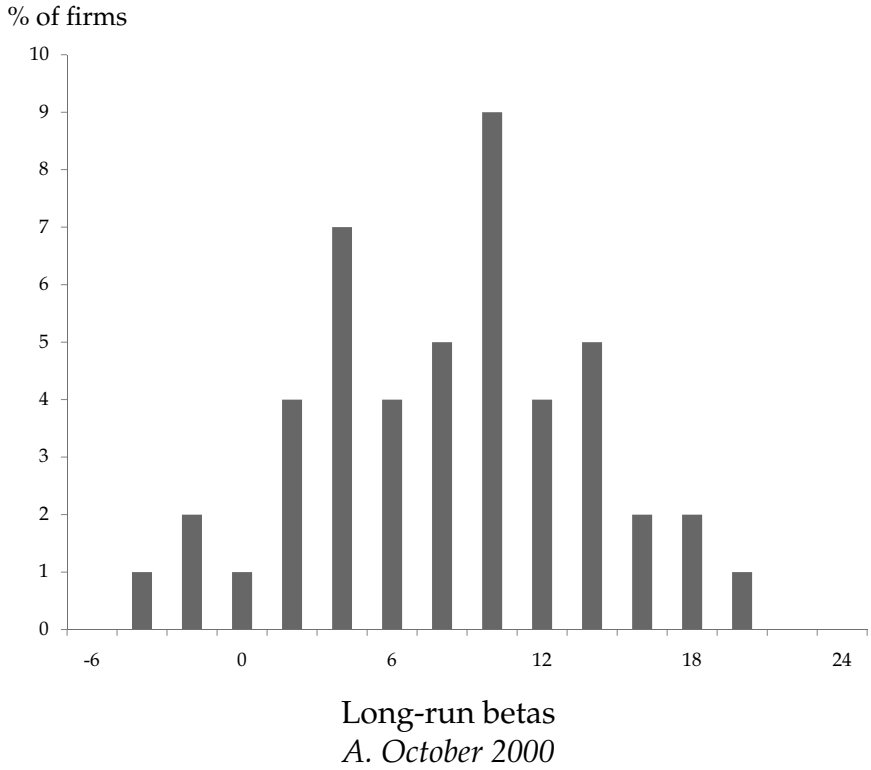
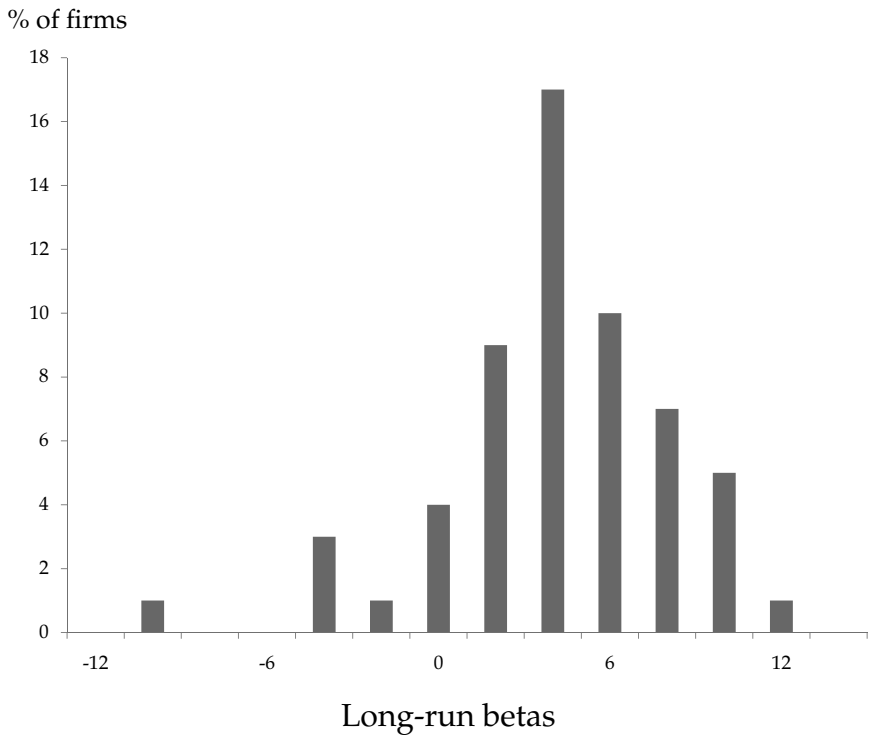


Fig. 2. Seven-year average rolling inflation betas and inflation hedging firms, January 2000-July 2012



A. October 2000



B. December 2008

Fig. 3. Cross-sectional distribution of long-run consumer prices betas within the S&P 500 universe, October 2000 and December 2008

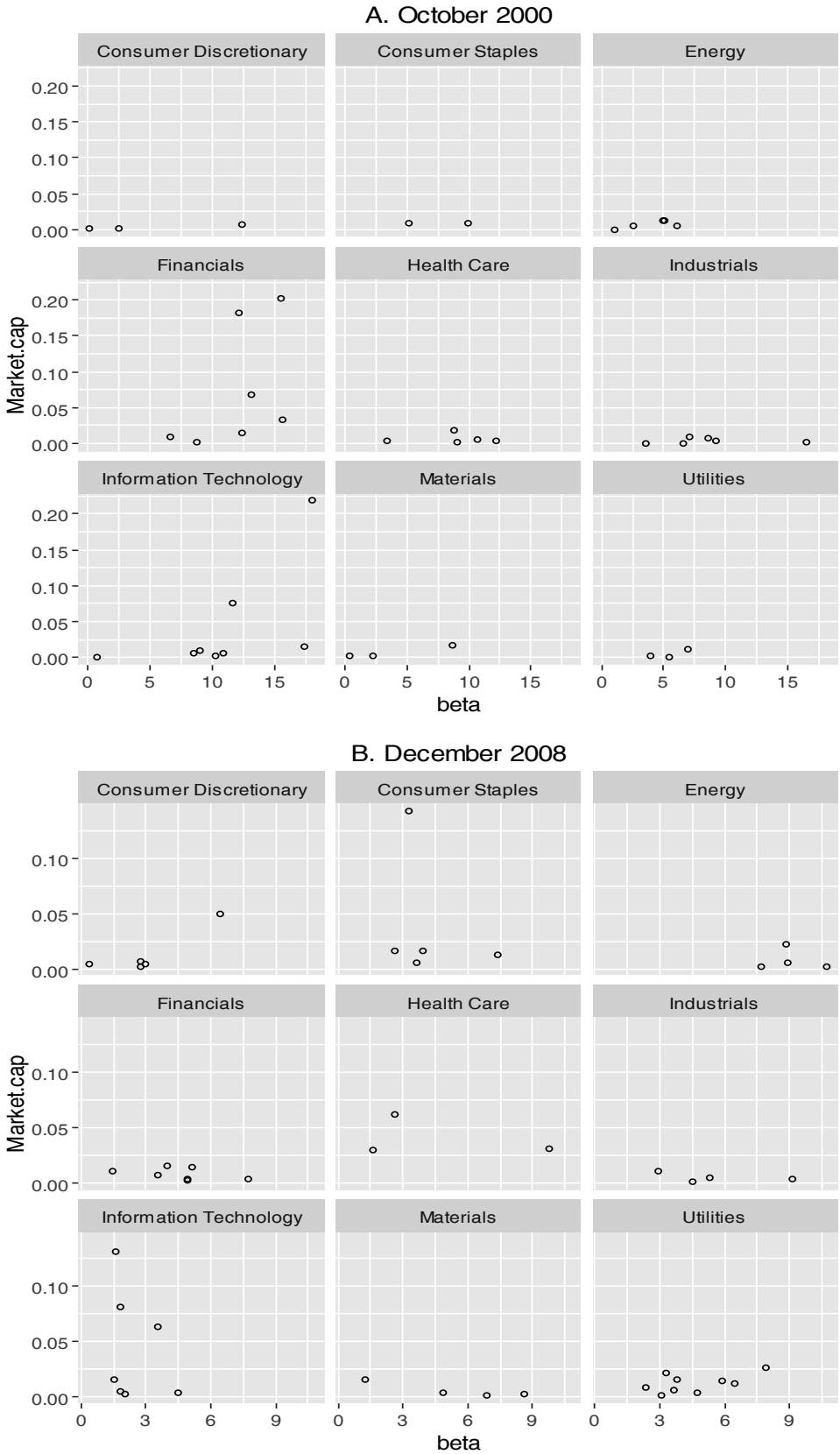
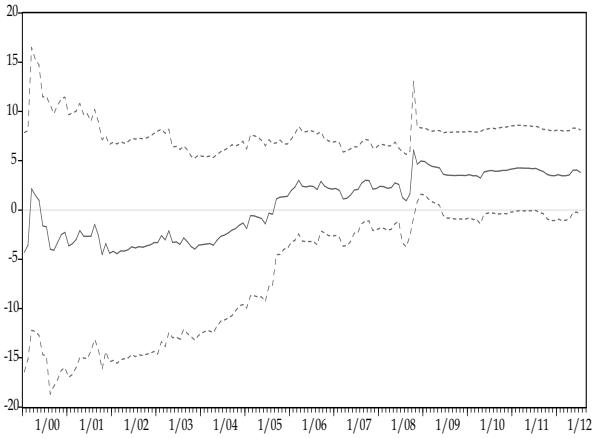
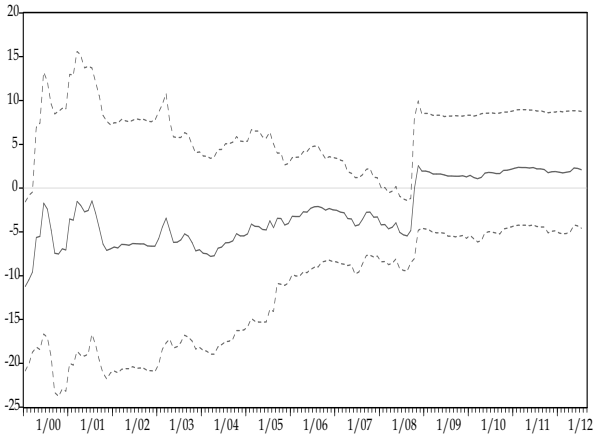


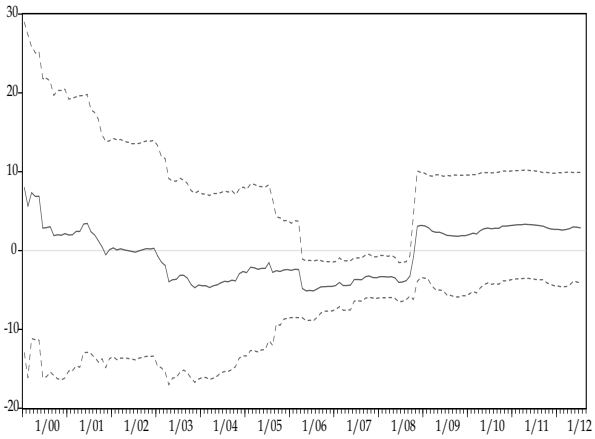
Fig. 4. Cross-sector map of the best long-run inflation hedging individual stocks, October 2000 and December 2008.



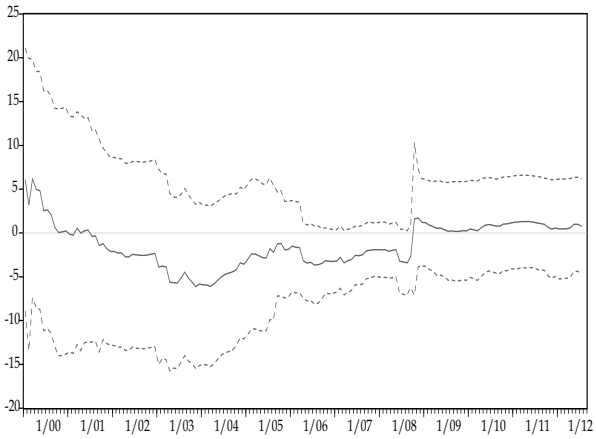
A. Energy



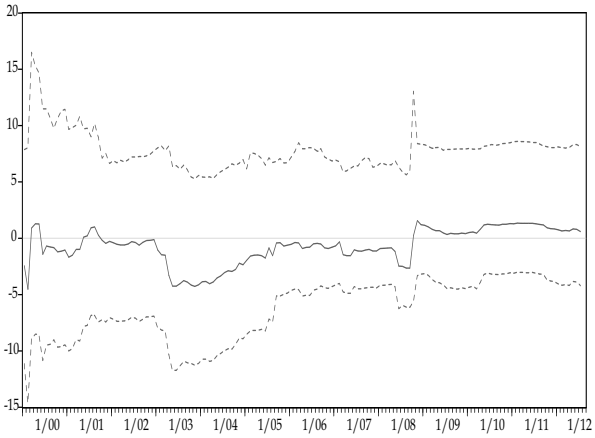
B. Information Technology



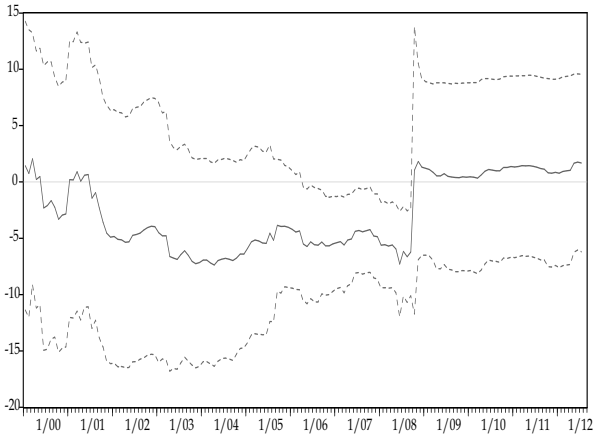
C. Materials



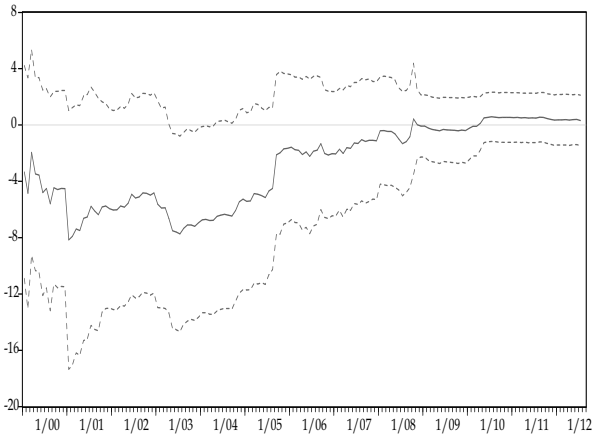
D. Industrials



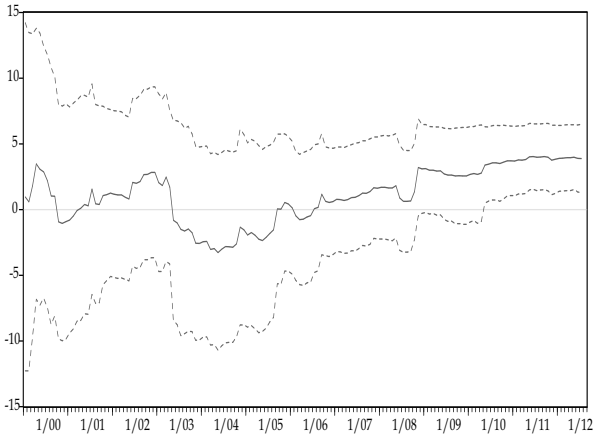
E. Financials



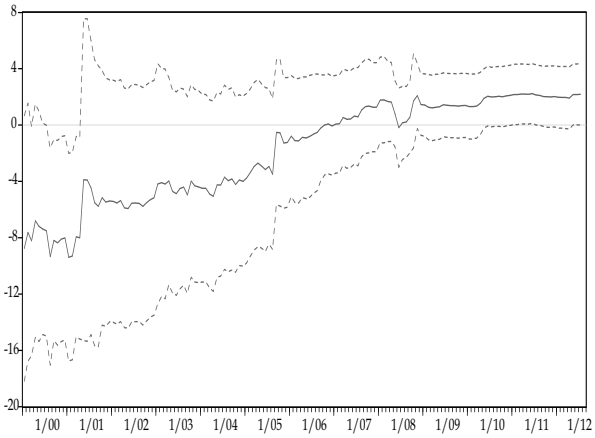
F. Consumer Discretionary



G. Utilities



H. Consumer Staples



I. Health Care

Fig. 5. Seven-year rolling inflation betas of S&P 500 sectors, January 2001-July 2012