5-2010

TWO ESSAYS ON HEALTH CARE COSTS AND ASSET RETURNS

Brian C. Payne
University of Nebraska - Lincoln

TWO ESSAYS ON HEALTH CARE COSTS
AND ASSET RETURNS

by

Brian C. Payne

A DISSERTATION

Presented to the Faculty of

The Graduate College at the University of Nebraska

In Partial Fulfillment of Requirements

For the Degree of Doctor of Philosophy

Major: Business

Under the Supervision of Professor John M. Geppert

Lincoln, Nebraska

May, 2010

TWO ESSAYS ON HEALTH CARE COSTS

AND ASSET RETURNS

Brian C. Payne, Ph.D.

University of Nebraska, 2010

Adviser: John M. Geppert

The first essay investigates whether health care is a priced factor in asset returns. Specifically, in the search for empirical relationships between macroeconomic factors and asset returns, health care appears to be a significant US economic force receiving less attention than others such as (aggregate) inflation, production, or consumption measures. We use the medical care component of the Consumer Price Index to measure medical inflation shocks as a candidate macroeconomic factor whose riskiness the market rewards. Incorporating multiple model specifications during the period 1967-2009, we find this inflationary component to be a relatively robust source of priced risk in US stock returns.

The second essay demonstrates how a genetic algorithm (GA) technique with standard parameters and the appropriate fitness function can generate five-asset portfolios that effectively hedge macroeconomic risks, including health care cost inflation. Investigating 40 macroeconomic series-year combinations, the GA generates 36 (11) hedging portfolios that are weakly (unambiguously) preferred to unmitigated risk exposure in an out-of-sample analysis between 2005 and 2008. This same technique can

create parsimonious mimicking or tracking portfolios for investable assets such as mutual funds and exchange-traded funds (ETFs), particularly in the down market of 2008.

Dedication

I dedicate this work, as with all my efforts, to my wife, Melissa, and our children. You are simultaneously my greatest heroes and biggest fans.

Acknowledgements

Thank you to my committee, Dr. John M. Geppert (Chair), Dr. Donna M. Dudney, Dr. Gordon V. Karels, and Dr. David B. Smith, for your time, energy, and assistance. In particular, completing this research would have been literally impossible without you, Dr. Geppert. In 17 years with the Air Force, I have met many, many patriots, public servants, and teachers; your commitment to this country, your community, and your students places you in the upper tail of the distribution. You exemplify the word "teacher," and I am forever indebted to you for mentoring me.

Dr. Jennings and Lieutenant Colonel (Retired) Fraser, you initiated my interest in this topic by allowing me to participate in your research. Thank you.

Mom and Dad, you taught me work ethic and perseverance and have endlessly supported me. I strive to become to my children a fraction of what you've been to me. You know how much you have impressed upon my life. Thank you.

Bob, Rita, and Mary, these past three years never would have occurred without you. You gave us a reason for being here and have supported our family for the duration. Thank you.

Uncle John, you uniquely know the instrumental, no *critical*, role you have played in this chapter of my life. I will forever remember it and hope to pay it forward someday. Thank you.

Jeff and Jirka, through this experience, in my vernacular, we have become "brothers-in-arms." Whether it was for personal or professional reasons, I have leaned on you both many times; you have never wavered. I will reciprocate anytime. Thank you.

To all of the other graduate students, before and after, I appreciate the individual roles you have played in my experience as well as the larger role you have played for the success of this department and program.   You include: Chris, Jeff, Jin, Stoyu, Lee, Rashiqa, Yi, Daria, and Thuy.

Lastly, but *most* importantly, I thank God. You are ultimately the source of all good things, and I am not worthy of the grace, guidance, and countless Blessings you have provided to me during this journey.

Grant Information

I would like to recognize and thank the U.S. Air Force and the U.S. Air Force Academy Department of Management for respectively funding and sponsoring this research. The views expressed here are solely mine and do not necessarily represent the views of these sponsors.

Table of Contents

Essay #1: Health Care as a Priced Factor in Asset Returns	1
Introduction	1
Why Medical Inflation?	2
Literature Review	3
Hypothesis Development	12
Methodology	13
Is medical inflation different from aggregate inflation?	13
Is Medical Inflation Different from Rm-Rf, SMB, HML, MOM, DEF, and TERM?	20
Estimates for Unexpected Medical Inflation	25
Results	29
Fama-MacBeth (1973) Two-Pass Method	29
Robustness Test: Characteristics-Based Medical Care Factor	40
Discussion	42
Conclusion	45
References	47
Appendix A: Figures	49
Appendix B: Tables	58
Appendix C: Using State Space Models to Disentangle Expected and Unexpected Inflation	92

Essay #2: Using Genetic Algorithms for Hedging Health Care Costs, Managing Macroeconomic Risk, and Tracking Investments 94

Introduction 94

Literature Review 95

Data 98

Genetic Algorithm Methodology and Proof of Concept 98

Applying the GA to Health Care Risk Exposure 105

Results 110

Extended Applications: Out-of-Sample Robustness Analysis, Other Macroeconomic Series, and Investable Assets 118

Out-of-Sample Robustness and Other Macroeconomic Series 118

Other Investable Assets: Mutual Funds and Exchange Traded Funds (ETFs) 125

Conclusions 133

References 136

Appendix A: Figures 137

Appendix B: Tables 152

Appendix C: Stock Numbers, Tickers, and Industries 167

List of Figures and Tables

Essay #1: Health Care as a Priced Factor in Asset Returns

Figure 1: Consumer Price Index (CPI) Measures, January 1967-August 2009 — 50

Figure 2: Monthly Joint Distributions of Inflation Components, Sorted into Quartiles — 51

Figure 3: Impulse Response Functions for Three-Variable Vector Autoregression (VAR) Model — 52

Figure 4: Monthly Joint Distributions of Potential Risk Factors, Sorted into Quartiles — 53

Figure 5: Plot of Actual (CPIAUCMO) vs. Expected (EXMEDINF) Aggregate Inflation using Kalman Filter Model, January 1967-August 2009 — 54

Figure 6: Plot of Actual (CPIMEDMO) vs. Expected (EXMEDINF) Medical Inflation using Kalman Filter Model, January 1967-August 2009 — 55

Figure 7: Acutal Medical Inflation and Expected Medical Inflation from Vector Autoregression Models, January 1967-August 2009 — 56

Table 1: Covariance/Correlation Tables for Inflation Series — 59

Table 2: Three-Variable Vector Autoregression (VAR) Estimates, January 1967-August 2009 — 60

Table 3: Three-Variable Variance Decomposition — 61

Table 4: Covariance/Correlation Tables for Various Factors — 63

Table 5: Eight-Variable Vector Autoregression (VAR) Estimates, January 1967-August 2009 — 64

Table 6: Eight-Variable Variance Decomposition — 66

Table 7: Covariance/Correlation Table for Various Measures of Unexpected Medical Inflation and Other Possible Proxies, January 1967-August 2009 — 69

Table 8: Fama-MacBeth (1973) Results for Priced Factors, January 1967-August 2009 — 70

Table 9: Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors-Chen, Roll, and Ross (1986) Mactoreconomic Factors, — 76

January 1967-August 2009

Table 10: Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors-Flannery & Protopapadakis (2002) Macroeconomic Factors, January 1967- August 2009 80

Table 11: Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors-Statistical Factors, January 1967-August 2009 84

Table 12: Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors-Including Medical HML Factor, January 1967-December 2008 88

Essay #2: Using Genetic Algorithms for Hedging Health Care Costs, Managing Macroeconomic Risk, and Tracking Investments

Figure 1: Monthly Consumer Price Index (CPI) Measures, January 1967-August 2009 138

Figure 2: Initial Population for Genetic Algorithm (GA) 139

Figure 3: GA Pairing Example 140

Figure 4: GA Proof of Concept Performance 141

Figure 5: Hedging Portfolio Examples 142

Figure 6: Division of the Data and Evaluation of Fitness 143

Figure 7: Genetic Algorithm Portfolio Performance for Out-of-Sample Period, January 2008-December 2008 144

Figure 8: Medical Inflation and Potential Hedging Portfolio Return Characteristics in Mean-Standard Deviation Space for Out-of-Sample Period, January 2008-December 2008 147

Figure 9: Mutual Fund and Potential Hedging Portfolio Return Characteristics, Mean-Standard Deviation Space, Out-of-Sample Period, January 2008-December 2008 148

Figure 10: Exchange-Traded Fund (ETF) and Potential Hedging Portfolio Return Characteristics, Mean-Standard Deviation Space Out-of-Sample Period, January 2008-December 2008 150

Table 1: Fitness Level for Asset Portfolios across Generations using Proof of Concept Returns, January 1967-August 2009 153

Table 2: Fitness Level for Asset Portfolios over Generations using Actual Target (Medical Inflation) and Investable Assets (303 Stocks from CRSP, Long Government Bond, Short Government Bond, and Treasury Bill), During the Test and Validation Periods, January 1967-December 2007 154

Table 3: Portfolio Hedging Effectiveness against Medical Inflation, Out-of-Sample Period, January 2008-December 2008 155

Table 4: Hedging Portfolio Performance in Funding $1M Health Care Liability, January 2008-December 2008 156

Table 5: Hedge Ratios for "Good" Genetic Algorithm Portfolio for Test Period, January 1967-December 2006 157

Table 6: Monthly Out-of-Sample Results for Macroeconomic Series of Interest Using, Annually-Established Policy Rule 158

Table 7: Monthly Out-of-Sample Results for Ten Random Mutual Funds Using Annually-Established Policy 163

Table 8: Monthly Out-of-Sample Results for Five Random ETFs Using Annually-Established Policy 165

Essay #1: Health Care as a Priced Factor in Asset Returns

Introduction

Health care represents a significant—and growing—portion of the US economy. Nationally, in 2009 health care spending is expected to reach $2.5 trillion, which represents over 17 percent of the gross domestic product (GDP). In other words, currently one of every six dollars spent in this country is health care related. This percentage has doubled over the past 30 years, and the Congressional Budget Office predicts it will double again over the next 25 years.[1] The impact of such health care costs can be catastrophic to individuals, as documented by Himmelstein et al (2009). They find 62 percent of personal bankruptcies filed in 2007 were linked to medical expenses even though nearly 80 percent of those filing for bankruptcy had health insurance. This rate of medical-cost-induced personal bankruptcies has increased by almost 50 percent since 2001.

Extrapolating this result from individual agents to the firms that compose the US financial market would indicate that firms with greater exposure to health care expenses should face higher risk of financial distress. One software CFO summarizes the risk of health care costs succinctly when he states, "Health-care costs are increasing faster than pretty much any other component of our cost structure…they have the potential to crowd out investment in other areas and ultimately make us less competitive."[2] According to portfolio theory, unless this risk is diversifiable across firms, investors should price this firm-specific risk and demand greater firm-specific returns for bearing it. The purpose of

[1] http://www.forbes.com/2009/07/02/health-care-costs-opinions-columnists-reform.html

[2] O'Sullivan, Kate, "All Eyes on Reform Public Support for Health-Care Reform is High, but Some CEOs Take Different View." *CFO* December 2009, pp. 38-43. This magazine is published by a subsidiary of *The Economist*.

this research is to determine the impact of health care costs on asset prices in the US market and to assess the degree to which medical costs are a priced risk in the US economy.

Why Medical Inflation?

The cost of medical care clearly affects firms in a non-trivial way. First, medical care appears to be a major component of labor compensation. According to the Kaiser Family Foundation's 2009 Employer Health Benefits Survey, employer-sponsored insurance covers 159 million nonelderly people, with the employer contribution averaging $9,860 per year.[3] This amount represents almost 74 percent of the $13,375 total average annual health care insurance premiums for family coverage, with workers themselves contributing the $3,515 balance. Also, data indicate medical care is a benefit provided by most publicly-traded firms. According to the same Kaiser report, 98 percent of firms with over 200 workers compensated employees by paying for some level of health insurance premiums in 2009. Over the past decade, rates have remained relatively constant in terms of the fraction of premiums paid by firms versus individuals and the percentage of individuals covered by large firms. Assuming competitive labor markets, these trends indicate a labor market demand for such coverage in these large firms, signifying firms have limited ability or desire to discontinue providing them. In fact, one CFO in a recent popular press article stated his firm must "continue to offer a competitive [health care compensation] policy…We see health care as an incredibly important

---

[3] http://ehbs.kff.org/

recruitment and retention benefit."[4] Consequently firms face medical care costs they cannot control yet must absorb due to their need to attract and keep high-quality labor. This trend appears valid for publicly-traded (i.e., larger) firms despite recent popular press reports that unaffordable premium increases for small businesses will likely decrease the amount they cover.[5] Thus it appears escalating medical care costs represent a reasonable candidate as a systematic risk to stockholders who hold publicly-traded firms.

Literature Review

For decades now research has sought to establish an empirical connection between macroeconomic events and stock price movements that theoretically ought to exist. This study extends the prior efforts that have documented a contemporaneous relationship between certain macroeconomic factors and returns. As we describe in more detail later, our focus on medical inflation augments previous findings regarding aggregate inflation. Studies show aggregate inflation surprises[6] and returns tend to be negatively-related over time (see, for example, Chen, Roll, and Ross (1986), Flannery and Protopapadakis (2002) and Hong, Torous, and Valkanov (2007)). Further, Chen, Roll, and Ross (1986) provide "weak" evidence that inflation is a priced risk factor, while the others do not investigate this result.

[4] O'Sullivan, Kate, "All Eyes on Reform Public Support for Health-Care Reform is High, but Some CEOs Take Different View." *CFO* December 2009, pp. 38-43. This magazine is published by a subsidiary of *The Economist*.
[5] http://www.gadsdentimes.com/article/20091025/ZNYT01/910253008?Title=Small-Business-Faces-Sharp-Rise-in-Costs-of-Health-Care
[6] Expected aggregate inflation can also have a negative relationship with returns depending on the time period and specification under study (see CRR (1986)).

Before summarizing the foundation of literature upon which this study will build, it is important to understand the difference between a factor explaining stock returns and the factor serving as a priced source of risk. While a macroeconomic factor, such as aggregate inflation, might exhibit high covariance with particular stock returns (i.e., have a high "beta" in a time series regression), this relationship does not say whether the market views this factor as a risky one worthy of return premia. In order for the factor to be considered risky, it is necessary for any security's "beta" to correlate with the security's excess returns in the cross-section. The Fama-MacBeth (1973) two-pass procedure represents the classical way to determine whether a factor is priced by the market. We will describe this procedure in more detail under the "Methodolgy" section.

The seminal study on the relationship between macroeconomic data and stock returns, Chen, Roll, and Ross (1986), investigates monthly stock returns between 1958 and 1984 with a goal of bridging the gap that existed between the theoretical idea that macroeconomic events drive stock prices at some level and the fact that nobody had found empirical evidence of such a connection. Specifically, the authors study whether industrial production, inflation (both expected and unexpected), a term risk premium (difference between return on long government bond and short Treasury bill), and a default risk premium (difference between return on portfolio of Bbb rated bonds and short Treasury bill) explain expected stock returns over time. They admit these macroeconomic series are by no means exhaustive in their inclusion. In briefly addressing other theoretical predictions and as a robustness test, the authors augment their model with the market risk premium, a measure of consumption, and an oil price

index (PPI for crude), ultimately concluding that the former has a negligible effect, and neither of the latter factors are priced.

Methodologically, CRR (1986) form twenty size-based portfolios whose returns are used as the dependent variables in their models, since using portfolios helps to mitigate errors-in-variables problems. They then implement a Fama-MacBeth (1973) two-pass methodology to assess whether the aforementioned macroeconomic factors are priced. While the inclusion of the market return—either value- or equal-weighted—performs well in the first-pass time series regressions, as we expect from the Sharpe (1964) and Lintner (1965) Capital Asset Pricing Model (CAPM), this factor is not priced in the presence of certain macroeconomic factors once the second-pass cross-sectional regressions are completed. The authors indicate that relatively smooth macroeconomic measures will inherently fail to explain a substantial amount of the variance in noisy stock returns. As a result, none of their models depict the coefficient of determination measure (i.e., "R-squared") for assessment. We anticipate similarly unimpressive R-squared values for our first-pass regressions that include only macroeconomic factors.

The consensus of this research is that industrial production, changes in the market risk premium, yield curve twists, and measures of unanticipated inflation and expected inflation changes are all significant in explaining expected stock returns. The effect of these variables on stock returns is robust to the inclusion of the market return factor (per CAPM) as well as to the inclusion of consumption and oil robustness variables. In sum, this study represents a hallmark effort in tying together the theory and empirical representation of macroeconomic events influencing stock returns.

In contrast to the study of macroeconomic factors, Fama and French (1993) study and find evidence of a parsimonious factor model that explains the variation in both stock and bond returns. Specifically, they contend that the following five factors explain the returns: excess market return (value-weighted market return minus one-month Treasury bill), SMB (Small-minus-Big, calculated by subtracting the return of the decile of the largest stocks—by market capitalization—from the decile of smallest stocks), HML (High-minus-Low, calculated by subtracting the return of the stock decile having the lowest book-to-market equity ratio from the decile with the highest book-to-market equity ratio), DEF (default risk premium, calculated by subtracting the long government bond from a Baa-and-below portfolio of similar duration corporate bonds), and TERM (term risk premium, calculated by subtracting the one-month Treasury from the long government bond).

These authors investigate monthly returns from 1963 to 1991 for 32 different portfolios of returns, which include 25 stock portfolios and 7 bond portfolios. They form the stock portfolios by intersecting the quintiles of size and book-to-market equity ratio. Their bond portfolios include two government portfolios, short- and long-term, and five corporate portfolios ranging in grade from Aaa to low-grade (or junk) bonds.

While their model is admittedly atheoretical and strictly empirically-founded, the Fama and French (1993) results are econometrically impressive. Their model parameters are highly statistically significant, and the coefficient of determination values are extremely large across the 32 portfolios. They do not price these particular factors in the traditional Fama-MacBeth (1973) two-pass manner, since they indicate adding bonds to the cross-sectional regressions would be difficult because “size and book-to-market

equity have no obvious meaning for government and corporate bonds." Instead of pricing their factors, the authors test for their cross-sectional effectiveness in the market by jointly-testing whether the intercept terms for all 32 portfolios are zero using the Gibbons, Ross, and Shanken (1989) methodology. While this test does not unequivocally support their model—mainly due to the small/low book-to-market portfolio having a non-zero intercept—their results indicate the factors explain stock and bond returns rather well. Finally, they perform a variety of robustness tests, including examining the January effect and bisecting the sample, and find the results tend to hold.

Since theory indicates macroeconomic factors should influence stock returns by serving as nondiversifiable risk factors (Ross (1976)), Flannery and Protopapadakis (2002) investigate the impact of 17 macroeconomic series on daily stock return mean and conditional volatility for the period between 1980 and 1996. Ultimately the authors confirm that inflation (CPI), the Producer Price Index (PPI), and a monetary aggregate (M1 and M2) influence stock returns, as previous research has indicated. Additonally, they make the novel discoveries that balance of trade (BOT), employment, and housing starts explain stock returns' conditional volatility. They determine news for these six variables is also associated with higher trading volume, an expected empirical result. Meanwhile, they fail to find influences from Industrial Production or GNP, as previous research has documented.

Their data set of macroeconomic series is arguably the most comprehensive to date, and the authors utilize a convincing means to measure the "surprise" component of the measures. Their method is important, because it is the surprise, or unexpected component, of macroeconomic data that should theoretically induce stock price changes,

or returns.[7] The authors measure surprise by using data from MMS International (now a subsidiary of Standard & Poor's) on analysts' expectations of macroeconomic data values for a given date. By comparing these expectations to the actual announced value, the authors quantify the surprise component. In using daily returns and volatility, the authors argue they can quantify most precisely the effect the news has on the market.

To mitigate criticism, Flannery and Protopapadakis (2002) employ various techniques. To avoid allegations of model misspecification, they include a host of conditioning variables, including: lagged market return, lagged risk-free rate, lagged junk bond premium (AAA-BAA returns), lagged term risk premium, lagged dividend-to-price ratio, lagged firm size value, and a host of timing controls to account for post-holiday returns and the January effect. Addtionally, they forestall the econometric problem of heteroskedasiticity by employing a generalized autoregressive conditional heteroskedasticity (GARCH) model to investigate returns.

We aim to augment and extend Flannery and Protopapadakis (2002) since (1) their study looks at aggregate inflation (versus medical inflation) as one of the macroeconomic series and (2) their study identifies priced factor candidates, but they never determine whether these candidates are priced. While we also confirm the negative relationship between contemporaneous inflation (and its surprise), we also investigate inflation's sub-component related to medical costs. Finally, whereas these authors determine which macroeconomic factors explain stock returns (and volatility) over time (i.e., they complete the Fama-MacBeth first-pass), our study investigates whether any

[7] Theory tells us factors proxy for the stochastic discount factor (SDF), which is a ratio of the present and expected future marginal utilities of consumption. Under the permanent income hypothesis, consumption is a random walk, which induces prices that necessarily deviate from expected levels and generate returns.

candidate factors we discover are indeed priced in equilibrium. That is, we complete both the first- and second-pass for the relevant factor candidates.

While prior studies have investigated contemporaneous macroeconomic variables' association with stock returns, Hong et al (2007) investigate the information diffusion theory by determining that certain industry returns lead the broad market returns. These authors determine that portfolios for retail, services, commercial real estate, metal, and petroleum forecast the stock market, in some cases by up to two months. Their finding is generally robust to the eight-largest non-US stock markets. Additionally, they relate their results to economic theory by discovering that industries that forecast the market also generally forecast two macroeconomic series (Industrial Production Growth and the Stock and Watson (1989) coincident index of economic activity) that explain returns.

Using monthly returns from 1946-2002, Hong et al (2007) investigate the ability of the Fama-French 38 industry sectors to explain broad market returns. Their intent is to test the information diffusion hypothesis (see Merton (1987) and Stein (1999)), which assumes that news travels slowly across markets and due to limited information-processing capacity, implying investors might not pay attention to or extract information from asset prices of industries they do not pay close attention to. Excluding five industries for missing data and generating a commercial real estate industry portfolio, the authors ultimately determine 14 of the 34 industries lead the market by one month. These industries are: commercial real estate, mines, apparel, print, petroleum, leather, metal, transportation, utilities, retail, money or financial, services, non-metallic minerals, and television. They interpret this finding as evidence that information diffuses less-than-

instantly across industry sectors to have an effect on the aggregate market and that information takes on the order of two months to be incorporated from industries into the broad market index. With respect to international data, the authors study returns for Japan, Canada, Australia, UK, Netherlands, Switzerland, France, and Germany for the period 1973-2002 and find the results hold up remarkably well.

These authors also control for similar factors as the other studies, specifically, lagged values for: excess market return, inflation, default spread (BAA-AAA), market dividend yield, and market volatility. Notably, these authors highlight that, "from the literature on stock market predictability that being able to predict next month's return is already quite an achievement, as it is notoriously difficult to predict the market at long horizons."

The gaps in this research we intend to fill are that health care is not an explicit US sector these authors studied, so its leading ability in the US is not clear. Notably, the other international stock markets studied have a health care sector, and its leading effect is unfortunately indeterminate based on the presented results. Additionally, our health care measure is a macroeconomic series versus a composition of returns series, so we are bridging a gap between leading indicators and macroeconomic factors that is not addressed in previous literature.

Another study, Lamont (2001), presents a purely atheoretical model to estimate, or track, non-investable macroeconomic series over time. The author uses 13 base assets and their lagged returns to track these macroeconomic series. The base asset series include four bond portfolios, eight industry-sorted stock portfolios, and the market portfolio for the stock market. The key macroeconomic series estimated include:

industrial production growth, real-consumption growth, real labor income growth, inflation, excess stock returns, excess bond returns, and Treasury bill returns.

To ensure he is not capturing the effect of other key variables known to predict stock and bond returns as well as the macroeconomy, he controls for nine lagged variables (with a constant term): Treasury bill returns, term premium for long-term government bonds (long bond yields minus Treasury bill), term premium for one-year government notes (one-year note yield minus Treasury bill yield), default premium on corporate bonds (BAA minus AAA yield), default premium on commercial paper (paper yield minus Treasury bill yield), the dividend yield on the CRSP value weight aggregate portfolio, 12-month production growth, CPI inflation, and excess stock returns. Ultimately, with partial R-squared values of between 0.04 and 0.23, Lamont (2001) concludes that, controlling for other known relationships, these investable portfolios do indeed track non-investable macroeconomic variables at some level.

The relevance of Lamont's study to this research assumes we find that medical inflation is a priced factor in security returns. If this result occurs, the natural next step will be to investigate ways firms can hedge the risk presented by medical inflation and its associated costs. Specifically, whereas Lamont analyzes the ability of these investable assets to track aggregate inflation, we look more closely at an investable portfolio's ability to track, or mimic, the behavior of medical inflation.

Finally, as a caveat to our anticipated results, one must consider these conclusions cautiously since the contemporaneous relationships documented are based on ex post corrected macroeconomic data, an issue highlighted by Christoffersen, Ghysels, and Swanson (2001). In their study, the authors demonstrate how markets adapt to

information as it is released, and unfortunately much macroeconomic data is initially released using preliminary, or estimated, values. Conducting studies after the fact can chronologically misalign ex-post corrected macroeconomic data with market events at a specific point in time. Thus while we price medical inflation using ex ante accurate data, the market might not have had these exact figures contemporaneously, so it is indeed possible that the relationships we demonstrate are perhaps skewed by the passage of time and the use of ex post data.

Hypothesis Development

Asset pricing theory (see Cochrane (2005) or Campbell, Lo, and Mackinlay (1996)) generates relationships between expected security returns and individuals' consumption as well as their investment opportunity set. That is, changes in security prices generate returns, and these changes are induced by events that alter individuals' ability to consume or their opportunities to invest. The most natural and intuitive events that alter these items are macroeconomic phenomena. For instance, higher-than-expected inflation affects investors' ability to consume, which should in turn affect the demand for stocks and influence their prices. As another macroeconomic example, a spike in unemployment would likely affect individuals' aggregate consumption and therefore theoretically affect stock returns. It's this theoretical relationship between macroeconomic phenomena and stock returns that forms the basis for this study.

Specifically, this study analyzes the macroeconomic phenomenon of medical inflation and its effect on security returns. Based on the relevance of medical care costs to the US economy, the fact that all firms with human capital appear to be exposed to this

cost, and the devastating effect these costs have had on some individuals (see Introduction for these details), this study proposes that medical care costs affect financial markets in a material manner, since they affect the riskiness of firm cashflows to the extent firms are exposed to medical inflation. Specifically, we hypothesize that the market prices firms' exposure to medical care costs as a source of systematic risk. Thus those securities whose returns covary positively with medical inflation should earn excess returns. We anticipate medical inflation surprises price negatively since those assets that covary positively with medical inflation shocks serve as hedging instruments against unanticipated spikes in health care costs.

Methodology

Is medical inflation different from aggregate inflation?

We first establish that although the Medical Care Consumer Price Index (CPI) is a component of aggregate CPI, its (unexpected) behavior is sufficiently different from the aggregate measure to warrant its consideration as a separate priced factor. Figure 1 plots the monthly time series from January 1967 to August 2009 of CPI for All Urban Consumers (CPIAUCSL), which we call aggregate CPI for brevity, and some of its major components. For future reference, Appendix A includes all figures, and Appendix B includes all tables. All levels in this study are seasonally-adjusted whenever possible. Specifically, series include Medical Care CPI (CPIMEDSL), Housing CPI (CPIHOSSL), Food and Beverage CPI (CPIUFDSL), and Transportation CPI (CFDTRNSL). These components currently represent almost 80 percent of the aggregate CPI, with the Medical component representing 6.39 percent, Housing 43.42 percent, Food 15.76 percent, and

Transportation 15.31 percent.[8] While the composition of aggregate CPI has certainly changed over time, these composition changes are not material for our purposes since our focus is on inflation in the medical component over time.

Our data sample begins in January 1967 since it represents the time when Medical CPI begins a trend of over 40 years of month-to-month variation. While data exist beginning in 1947, data for two key factors, DEF and TERM, only becomes available beginning in April 1953 when the 10-year government bond data originated. More importantly, Medical Care CPI exhibits 108 months of zero changes in those first 238 months of measurement, which is almost 50 percent of the time and clearly deviant behavior considering the more recent pattern of consistent upward monthly variation. The sample ends in August 2009, for a total of 512 months of data.

While a visual analysis of all panels of Figure 1 shows that medical CPI levels clearly diverges from the other displayed CPI components beginning in approximately 1985, statistical tests of the relation between aggregate and medical CPI further confirms this observation. Dickey-Fuller tests for unit roots indicate all subject CPI series are integrated of order 1, or I(1), for all time periods shown, yet none of them are cointegrated either pairwise or as a group. Therefore, to work with stationary series, from here we will use the monthly percent changes in these series. We use the term "inflation" to refer to percent changes in a particular CPI measure (e.g., monthly medical inflation represents the monthly percent change in medical CPI). To calculate per period percent changes we difference the natural log of the levels. For internal consistency, we also convert any discrete returns to their continuous values throughout this study. All

[8] For data availability and relevance reasons, we omit data on Apparel (3.69 percent), Recreation (5.74 percent), Education and Communication (6.30 percent), and Other goods and services (3.39 percent).

monthly and quarterly percent changes are stationary according to Dickey-Fuller tests, with the exceptions coming in annual sampling where Food and Transportation inflation maintains a unit root.

Estimate of the joint distribution

Our first test of statistical independence or difference between aggregate (and other types of) inflation and medical inflation involves an estimate of their joint distribution using a one-thousand iteration bootstrap simulation. In this simulation, our goal is to determine whether the actual joint distribution of the monthly time series of medical inflation and aggregate inflation differs from a joint distribution created if these series were independent. The procedure for the simulation involves first placing medical inflation values into quartiles. Next, the values for a second time series are placed into quartiles. We create a 4 x 4 grid that contains the counts of each quartile intersection. For instance, if the lowest values of medical inflation (i.e., quartile 1) intersected with the lowest values of aggregate (i.e., quartile 1) 54 times, then the count in cell (1, 1) equals 54, as we see in Figure 2. Next we randomly reorder monthly aggregate inflation values and match these random values with the quartile of the corresponding monthly medical inflation value. To determine whether the actual correspondence occurs more or less frequently than if the series were independent, we average the count of the random pairings over the 1000-iteration bootstrap simulation. It is then possible to determine whether the actual pairing count is in the tails of the random pairing count.

Figure 2 depicts the quartile-by-quartile average results for one-thousand iterations comparing monthly medical inflation to others. All monthly pairings are

represented, and thus the sum of all cells equals our 512-month dataset. Shaded cells differ from a "random" value by occurring with extremely high (bold and shaded) or low (underlined and shaded) frequency. We use $\alpha = 0.10$ on each side to determine the non-random pairings.

Figure 2 indicates that monthly medical inflation is positively related to monthly aggregate inflation, especially at the extreme values (quartiles 1,1 and 4,4), which makes sense since (a) medical inflation is a component of aggregate inflation, and even with its low weighting within aggregate inflation, extreme values will magnify its affect on aggregate inflation and (b) it is also positively-related—albeit to a lesser extent—to Housing inflation, Food inflation, and Transportation inflation, which are obviously also components of the aggregate inflation measure. The bold (underlined) cells indicate where the cell values are above (below) the 90^{th} percentile values for that cell across the one-thousand bootstrapped iterations.

This positive relationship is also shown using Table 1, which shows the various monthly inflation correlations on the upper triangle. Variances (covariances) are on the diagonal (lower triangle). For example, Panel A indicates a correlation of 0.405 between aggregate inflation and medical inflation. Monthly medical inflation is less correlated with aggregate inflation than it is with housing inflation. While the correlation with food and transportation inflation is still positive, these values are lower yet. As one would expect, the correlations all grow monotonically as the measurement frequency decreases, or time horizon increases, to quarterly and annual data. Interestingly, across all sampling frequencies, medical inflation has the lowest variance, with the variance measures located on the diagonal. Coupled with the time series level plots in Figure 1, this result indicates

medical inflation appears to be moving upward at a relatively constant rate relative to the other inflation measures. On the contrary, transportation inflation exhibits much higher volatility than the other measures across all sampling frequencies.

While monthly medical inflation is contemporaneously positively related to aggregate inflation and its major components, contemporaneous medical and aggregate inflation are not ultimately our primary variables of concern. Since theory argues the market imputes any expected information into returns, it is the surprises in these variables that should truly impact stock returns. Therefore it is the correlation between these surprises, or shocks, that matter most. While we explicitly address this relationship next, to foreshadow, the respective correlations are much lower among surprises irrespective of the measurement method we use.

VAR decomposition

Given the inherent and exhibited contemporaneous relationship between medical inflation and aggregate inflation coupled with our inability to create a compelling rationale for one exogenously determining the other, we believe each to have an autoregressive component as well as an explanatory component that includes lagged values of the other inflation factor. Additionally, since we are ultimately interested in these inflation factors' affect on the stock market, one method to get surprises involves using a vector autoregression model (VAR) that incorporates these three variables. Specifically, we estimate the VAR model in equations (1) to (3) to determine how similar or different the relationships between medical and aggregate inflation are with respect to the market.

$$CPIMEDMO_t = \alpha_0 + \alpha_{1,i}CPIMEDMO_{t-i} + \alpha_{2,i}CPIAUCMO_{t-i} + \alpha_{3,i}MKTRF_{t-i} + u_t \quad (1)$$

$$CPIAUCMO_t = \beta_0 + \beta_{1,i}CPIMEDMO_{t-i} + \beta_{2,i}CPIAUCMO_{t-i} + \beta_{3,i}MKTRF_{t-i} + v_t \quad (2)$$

$$MKTRF_t = \delta_0 + \delta_{1,i}CPIMEDMO_{t-i} + \delta_{2,i}CPIAUCMO_{t-i} + \delta_{3,i}MKTRF_{t-i} + w_t \quad (3)$$

where $CPIMEDMO_t$ ($CPIAUCMO_t$) represents monthly medical (aggregate) inflation for month t, $MKTRF_t$ is the market risk premium[9], and u_t, v_t, and w_t represent the residuals, which we treat as the "news" or surprise component of each series.

Medical inflation represents its own niche of products and services that are uniquely influenced by their industry- or market-specific cost changes. But the medical care industry also utilizes products and services common across industries, and the cost inflation these items experience is best represented by the lagged cost changes of the entire market basket of goods. We easily could have proxied the aggregate inflation component with its non-medical subcomponents (e.g., Food, Housing, Transportation, etc.), but doing so should yield analogous results with perhaps less precision due to the loss in degrees of freedom. Similar logic holds for explaining aggregate inflation. We do not necessarily anticipate the market risk premium will affect our inflation measures, however, we include this variable in the VAR to allow for discerning differences between lagged medical and aggregate inflation measures on stock market returns.

Table 2 summarizes the outputs from this VAR model, which uses the Schwarz criterion to determine the appropriate lag length of 2. From Column 3, labeled "CPIAUCMO," the market risk premium significantly leads aggregate inflation by one

[9] Taken from Ken French's data library:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

month. On the other hand, it does not have a relationship with medical inflation. Instead, both one- and two-month lagged medical and aggregate inflation explain current medical inflation. Medical inflation leads aggregate inflation by two months, while aggregate inflation is autocorrelated at one month, controlling for the other variables' influences. Finally, only the one-month lagged market risk premium has any explanatory power for the current market excess return.

Impulse response

The plots in Figure 3 show the univariate impulse response functions among these variables. Specifically, these plots demonstrate the 18-month effect of a one standard deviation shock to each variable along with the asymptotic standard error confidence bands. Plots (1,2) and (2,1) are of primary interest, as they indicate that a univariate shock to medical or aggregate inflation has a two- to three-month upward effect on its counterpart. But this upward effect reverses and eventually dies out over the ensuing 15 months. Thus a shock to medical (aggregate) inflation has no permanent effect on aggregate (medical) inflation according to the results from this model. So despite the relationship between aggregate and medical inflation that occurs by-construction, this result provides some of the strongest evidence to this point that medical and aggregate inflation can be considered different macroeconomic phenomena.

Variance decomposition

While the impulse response functions demonstrate the results of a unilateral shock to a particular variable on another variable, for example, the timing and magnitude of a

shock to aggregate inflation on medical inflation, it is also constructive to view the variance decomposition. Using the Choleski variance decomposition method and ordering by medical inflation, aggregate inflation, and market risk premium, we can determine the composition of medical inflation's variance over time attributable to shocks to itself, shocks to aggregate inflation, and shocks to the market risk premium. Table 3 depicts this decomposition.

These results further support the relationship between aggregate and medical inflation found in the VAR outcome and impulse response functions. Specifically, by 18 months after a shock to medical inflation, fully 86 percent of the variance in medical inflation is driven by its own behavior. Alternatively, 13.6 percent is driven by the variance in aggregate inflation, and less than 1 percent by the variance in the market risk premium. These results are not sensitive to the variables' ordering. Thus it appears that aggregate inflation's variance is not the major force driving medical inflation's variance, and we have more evidence that these two series are separate phenomena despite their inherent relationship. It becomes apparent later that the market perceives the associated risk differently as well.

Is Medical Inflation Different from Rm-Rf, SMB, HML, MOM, DEF, and TERM?

To explore whether medical inflation is a priced risk factor in stock returns, it is also worthwhile ensuring it does not simply proxy for factors already known to perform well in explaining stock returns. Specifically, Fama and French (1993) demonstrate the efficacy of their well-known SMB and HML factors to explain the time series of stock returns. Additionally, they echo the CRR (1986) findings that DEF and TERM have

important relationships with stock returns. While CRR (1986) find DEF and TERM are priced risk factors in stock returns, Fama and French (1993) find these two factors help generate a more unifying model to explain time series returns of both stocks and bonds, not solely stocks as approached in CRR (1986). Finally, we look at the relationship between medical inflation and Momentum (MOM), initiated by Jegadeesh and Titman (1993) and implemented by Carhart (1996 and 1997) to help explain stock returns.

For this section, we collect SMB, HML, and MOM values from Ken French's data library. We calculate the default risk premium, DEF, as the difference between the monthly Moody's seasoned Baa corporate bond yield and the 10-year Treasury constant maturity rate. TERM represents the term risk premium, or by-month difference between the 10-year Treasury constant maturity rate and the three-month Treasury bill. For these measures we obtain the Baa portfolio, long government bond, and three-month Treasuries after January 1995 from the *Federal Reserve Statistical Release H.15, Selected Interest Rates*. We are gratefully acknowledge Jeffrey Pontiff for providing pre-1995 data on the three-month Treasuries.

Joint distribution

Analogous to the bootstrapping method employed above, Figure 4 shows the quartile joint distributions between medical inflation and various factors. The only real potential for a relationship between medical inflation and known factors occurs with the term risk premium (TERM). While a clear negative pattern fails to emerge, the abundance of abnormally high and low contemporaneous relationships (10 of 16 cells) is concerning. Although the relationship is not as pronounced as we anticipated, this

indication of some relationship is not surprising given that TERM effectively represents the difference between the limits of the yield curve, which many interpret as an indicator of future inflation. To the extent the market interprets current high inflation as unsustainable going forward, one would expect the somewhat negative relationship we observe. A consistent result occurs in the final grid, which indicates that medical inflation's negative relationship with TERM is similar to the relationship between aggregate inflation and TERM. This result becomes evident by comparing the bottom two results in Figure 4.

Figure 4 indicates the relationship of SMB, HML, MOM, and DEF with medical inflation is virtually no different than a random pairing of the monthly values. While DEF shows some slight evidence of a positive relationship with medical inflation, a confounding result is that DEF is also high when medical inflation is low an abnormal amount of time (see sector 1,4).

The correlations in Table 4, which again contain the correlations in the upper triangle and covariances on the diagonal and lower triangle, show medical inflation is not very correlated with any of the other previously-demonstrated factors using monthly sampling. Again, the absolute values of the correlations generally grow monotonically as the sampling frequency decreases. Medical inflation once again has the lowest variance of all factors studied in this section. The other notable facts from Table 4 are that once again medical inflation is much less volatile than the other measures, and also the excess market return, MKTRF, has a variance is generally larger than the other factors. Thus even though medical inflation might be related to other factors, as CRR (1986) highlight, we must consider the relative volatility of various macroeconomic series. Specifically, at

the monthly frequency, the next least volatile factor, DEF, has a variance (0.548), which is over seven times that of medical inflation (0.073). The other factors have variance values greater than medical inflation by two orders of magnitude. Thus if the visual, bootstrapping simulation, and correlation results are not enough to separate medical inflation as its own factor, then its relative smoothness over time should suffice. This smoothness could prove detrimental, as prior authors have pointed out the consequent challenge of such relatively "smooth" macroeconomic series having much explanatory power considering the highly-varying nature of asset returns.

VAR analysis

Akin to our earlier VAR analysis that includes inflation and the market risk premium, in this analysis we expand the VAR model to include the factors considered in this section that may explain and influence medical inflation. In addition to aggregate inflation and the market risk premium, we augment the VAR with SMB, HML, MOM, DEF, and TERM. Thus our system is represented by the following:

$$Z_t = \Gamma Z_{t-1} + u_t$$

where Z_t is an (8 x 1) state vector that includes medical inflation, aggregate inflation, market risk premium, SMB, HML, MOM, DEF, and TERM, Γ represents the (8 x 8) matrix of parameters, assuming we use one lagged value as explanatory variables, and u_t is the (8 x 1) vector of error terms for each respective variable in the state vector. In our case, the time series of u_1 is the variable of interest: unexpected medical inflation. To

clarify the above description, equation (4) illustrates the first equation (of 8) represented by the entire VAR system.

$$CPIMEDMO_t = \alpha_0 + \alpha_{1,i}CPIMEDMO_{t-i} + \alpha_{2,i}CPIAUCMO_{t-i} + \alpha_{3,i}MKTRF_{t-i} + \alpha_{4,i}SMB_{t-i} + \alpha_{5,i}HML_{t-i} + \alpha_{6,i}MOM_{t-i} + \alpha_{7,i}DEF_{t-i} + \alpha_{8,i}TERM_{t-i} + u_t \quad (4)$$

Using the Schwarz criterion to determine the appropriate lag length of 1, Table 5 depicts the VAR parameter estimates for this specification.

These results indicate that besides medical inflation itself, only aggregate inflation leads medical inflation by one month, controlling for the other lagged factors. We anticipated this result based on the earlier three-variable VAR, which showed the relationship to aggregate inflation. Lagged medical inflation does not have explanatory power for any of these other factors except for aggregate inflation and TERM, both of which it significantly leads by one month.

The variance decomposition reported in Table 6 shows the major source of variance over time for medical inflation stems from its own volatility (88.7 percent). The next major source of variance is aggregate inflation (9.1 percent), followed by MKTRF, HML, and TERM, which change slightly depending on the variable ordering, however, not substantially enough to warrant further comment. While the low self-values for DEF and TERM might initially cause concern, these values are order-sensitive and change dramatically when moved forward within the system. In general for all these variables,

order matters, and shocks to their own values persist over time. In untabulated results, the volatility in the market risk premium plays the major secondary role for these factors.

Estimates for Unexpected Medical Inflation

While medical inflation itself is noteworthy due to its markedly different behavior than aggregate inflation and arguably direct influence on firms' financial performance, theory predicts that the market has already imputed the expected medical inflation level into prices. Thus if the only medical inflation that occurs is at the expected level, then prices (i.e., returns) will not change based on this information. However, if medical inflation rises or falls in an unexpected manner, then to the extent this information affects either cash flows or their riskiness, prices ought to react accordingly and generate the commensurate returns. Since we know stock prices do indeed change often, and we suspect medical inflation plays a role in these changes, we are critically concerned with the effect of unexpected medical inflation on stock prices.

There exist multiple methods to disaggregate medical inflation into its expected and unexpected components, each with its own advantages and drawbacks. One alternative, along the lines of Fama and Gibbons (1982), is to decompose medical inflation into its expected and unexpected components using a time-varying parameter model. They implement this technique through a Kalman Filter econometric method based on a procedure originally described by Ansley (1980). Although Fama and Gibbons (1982) disentangle expected and unexpected aggregate inflation, we extend their implementation and apply it to medical inflation. The criticism with this method is clearly that aggregate inflation differs from medical inflation (as we argued in an earlier

section), and as a result, the Fisher (1930) relationship between aggregate inflation and interest rates does not necessarily hold for its components, such as medical inflation. The advantage of its straightforwardness is evident. For completeness, Figure 5 shows the plot of actual aggregate inflation (CPIAUCMO) and expected aggregate inflation (EXPINF) using this Kalman Filter method. Expected aggregate inflation (EXPINF) is clearly a smoothed version of the more volatile actual inflation (CPIAUCMO) series.

The other readily-available alternative we analyze is to estimate the VAR model along the lines of those we have created in earlier sections and use the residual from equations (1) and (4), u_t, as the unexpected component of medical inflation.

State space estimate

The first method we investigate here is the state space estimate, in which we use the same time-varying parameter Kalman filter model as Fama and Gibbons (1982) to generate expected and unexpected medical inflation. Please see Appendix C for a description of this method based largely on the presentation in Hamilton (1994a). For visual analysis, Figure 6 depicts the resulting time series plot of actual (CPIMEDMO) and expected (EXPMEDINF) using this technique.

Visual inspection indicates the estimate of expected medical inflation is a smoothed version of the more volatile actual medical inflation values, analogous to the more theoretically-based results for aggregate inflation in Figure 5. Given the lack of available alternatives for disaggregating expected and unexpected medical inflation, this similarity encourages us that while our decomposition of medical inflation into its components is not strictly based on the Fisher (1930) relationship like aggregate inflation,

the similarity of medical inflation's behavior to aggregate inflation's using this technique encourages us this method is not entirely inappropriate.

VAR estimate

Using the earlier VAR models, which we will refer to as the Inflation VAR (3 variables: CPIMEDMO, CPIAUCMO, and MKTRF) and the Factor VAR (8 variables: CPIMEDMO, CPIAUCMO, MKTRF, SMB, HML, MOM, DEF, and TERM), we create two series of unexpected medical inflation using the residuals from the first equation in each VAR specification. Figure 7 shows, respectively, a time series plot of the expected medical inflation values from the Inflation VAR (EXPMED3VAR) and Factor VAR (EXPMED8VAR) juxtaposed with the actual medical inflation (CPIMEDMO) time series. These results indicate the expected medical inflation tracks actual medical inflation quite closely, with the exception of a few deviations in the early-1980s and late-1990s.

Table 7 summarizes the relationships between our various measures of unexpected medical inflation and other key variables of interest by quantifying the correlations between these various measures and some of the key variables we are concerned might demonstrate redundancy with medical inflation.

Whereas previous results indicate a possibility that medical inflation might simply pick up the effect of aggregate inflation or perhaps even the TERM risk premium, the correlations between our various measures for medical inflation surprises and these variables are nearly zero per Table 7. The reason for the slight difference between some of these results and Table 1 is the loss of observations with the lagged terms in the VARs.

These results provide more compelling evidence that surprises in medical inflation, which might affect stock returns, do not simply reflect previously-documented factors that have been shown to explain returns. Again, our measures of medical inflation surprises are the Kalman Filter series (UNEXPMEDKALMAN), the Inflation VAR residual series (UNEXPMED3VAR), and the Factor VAR residual series (UNEXPMED8VAR). While aggregate inflation earlier proved to be our chief concern for redundancy with a positive correlation of 0.404, the correlations between the medical inflation surprises generated by the Kalman Filter and VAR models are much lower, ranging from 0.009 to 0.119. Further, none of the medical inflation shock measures are correlated with aggregate inflation shocks (correlations from -0.024 to 0.003). Recall that CRR (1986) show aggregate inflation is (mildly) priced in returns. Additionally, the relationships between medical inflation and TERM are effectively zero (ranging from -0.002 to 0.003). Finally, it is encouraging that all measures of unexpected medical inflation are highly-positively correlated with one another (between 0.853 and 0.892). In other words, the medical inflation surprises appear quite insensitive to the mechanism used to generate them, and they are not correlated with other factors that prior research has explored.

Given these results in Table 7, we proceed using only the unexpected medical inflation from the state space model (UNEXPMEDKALMAN) time series. This time series is most nearly orthogonal to both aggregate inflation and TERM, which to this point have been the factors of greatest concern in terms of redundancy.

Results

Fama-MacBeth (1973) Two-Pass Method

Having established unexpected medical inflation as a distinct factor from others that have shown an association with US stock returns in past studies, the next step is to determine whether it is priced in equilibrium. To do so, we employ the Fama-MacBeth (1973) two-pass method of time series and cross-sectional regression models. To minimize the errors-in-variables problems with individual stock returns, we use portfolios to measure returns. Specifically, we use the 25 Fama-French portfolio returns, which are formed by independently-sorting all NYSE, AMEX, and NASDAQ stocks available on CRSP into quintiles based on size and book-to-market ratio.[10] In the first pass, we use 60 months' of time series returns to generate betas according to equation (5).

$$R_{p,t} = \alpha_0 + \sum_{i=1}^{k} \beta_{p,i} Z_{i,t} + u_t \quad (5)$$

where $R_{p,t}$ is the month t excess return on portfolio *p*, *p* = 1,…,25, *t* represents 60 months' worth of time series data, *k* represents the number of factors, and Z_i represents a factor used to explain returns. $\beta_{p,i}$ represents a portfolio-specific parameter estimated in the model and is calculated as the covariance of the factor and portfolio return normalized by the variance of the factor (i.e., $\beta_{p,i} = cov(R_{p,i}, Z_i)/var(Z_i)$).

We then cross-sectionally price these betas monthly over the ensuing 12 months according to equation (6).

[10] We gratefully acknowledge Ken French's data library for providing these returns: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

$$R_{p,t} = \lambda_0 + \sum_{i=1}^{k} \lambda_{i,t}\beta_{p,i} + u_t \quad (6)$$

This analysis occurs on a rolling basis, beginning with 60-month beta estimation from January 1967 to December 1971, followed by cross-sectional regressions from January to December 1972. We then increment the beta estimation period by 12 months, re-calculate the betas using equation (5), and re-price the factors using equation (6). With data beginning in January 1967 and ending in August 2009, we ultimately have just under 38 years' worth of monthly risk prices (λ_i), or 452 monthly observations. Calculating the statistics on these risk price series allows us to determine whether the price of risk for the respective factor differs significantly from zero. In other words, for each unit of factor "risk," the associated coefficient quantifies the extra return required for bearing such risk.

We determine whether medical inflation is a priced risk factor using a variety of specifications. First and most simply, we include medical inflation expected and unexpected components as the only factors and then add aggregate inflation components. Next, we augment the CRR (1986) model specifications to include medical inflation components. Additionally, we extend the more recent results of Flannery and Protopapadakis (2002), explicitly pricing those macroeconomic series they indicate perform well in a first-pass scenario and further augmenting these measures with medical inflation. Finally, in a sort of hybrid macroeconomic-characteristics model, we price the Fama and French (1993) five factors, include momentum, and augment these factors with

medical inflation. Generally speaking, it appears medical inflation in some form loads as a priced risk factor across the model frameworks.

Two-pass method with unexpected medical inflation (and unexpected aggregate inflation)

Table 8, Panel A contains the results for the first set of second-pass regressions. Specifically, this table shows the second-pass results for 6 different model specifications having completed first-pass regressions for the period January 1967 to August 2009, or 512 months.

To get a baseline on our model's performance for the subject period, the first specification includes only the market excess return (i.e., simple single-factor CAPM), both for the first-pass time series regressions and the second-pass. To provide an example of the first-pass results from equation (5), we present Table 8, Panel B. It shows first-pass results across the entire time period (512 months), while the rolling regression methodology used in Table 8, Panel A runs the first pass time series regression for sixty months at a time. The results in Panel B, columns 4 through 6 indicate that the market risk premium explains each of the portfolio returns well across the entire time series (see the high t-statistics and coefficients of determination).

Turning back to Table 8, Panel A, the second column shows that in our period of study, the market risk premium factor is indeed priced in equilibrium during this period. While contrary to theory, we find a well-known empirical result that covariance with the market statistically has a negative return premium, which is opposite of that predicted by the Sharpe-Lintner Capital Asset Pricing Model. This result indicates the market risk premium is negative, or that this sample has a negatively-sloped Security Market Line.

As pointed out by Ahn, Gadarowski, and Perez (2009), this result could simply be an artifact of the relatively constant beta values (range from 0.81 to 1.45) across the 25 portfolios. Unfortunately such a negative-sloping Securities Market Line (SML) is a commonly-found but theoretically-discouraging result.

The first novel two-pass test we complete involves only expected and unexpected medical inflation as the possible risk factors. Table 8, Panel C, shows results from the associated first-pass regressions, which are analogous in format to those for the market factor shown in Table 8a.

From the first-pass regressions, it is evident that while the market risk premium is contemporaneously highly-positively correlated with each portfolio's returns, the same cannot be said of the contemporaneous relationship between medical inflation (expected or unexpected) and the portfolios' returns from the first-pass regressions. Like the market risk premium, which is statistically priced (Table 8, Panel A, Column 2), the results for medical inflation indicate the contemporaneous expected and unexpected medical inflation are both priced at conventional statistical levels (Table 8, Panel A, Column 3). Additionally, results for unexpected medical inflation (Column 4) are robust to the replacement of expected medical inflation with its first difference series, the analog to the change in expected aggregate inflation used in the CRR (1986) study. The fourth specification (Column 5) in Table 8, Panel A, which substitutes aggregate inflation expected and unexpected components for medical inflation, demonstrates that neither expected nor unexpected aggregate inflation are priced when used alone in the model. Finally, and perhaps most notably, medical inflation's loading as a priced risk factor is robust to including aggregate inflation components as factors in the fifth specification

(Columns 7 and 8). While the economic price of medical inflation decreases substantially when including aggregate inflation as a factor (from 0.10 to 0.05), unexpected medical inflation is nonetheless priced at conventional significance levels whether one uses the time series of expected medical and aggregate inflation or their first differences. Since Dickey-Fuller tests confirm that expected medical inflation (EXPMED) is a stationary time series, we proceed using it in future specifications versus the change in it.

While concerns about multicollinearity clearly arise when including both aggregate and medical inflation in the same model, the robustness of medical inflation's pricing both alone and despite the potential multicollinearity is encouraging. And we know the relationship between unexpected medical inflation, the variable of primary interest, is effectively uncorrelated with the other inflation measures. Overall, these models that incorporate medical inflation in relatively simple specifications entice us to explore more comprehensive specifications for evidence of medical inflation as a priced risk factor.

Although it is encouraging that the medical inflation factor prices in equilibrium during this period of study, one surprise result is that this factor prices positively. As with aggregate inflation, it seems most plausible that as stock (or portfolio) returns covary positively with medical inflation, then these assets would represent hedges for the "bad" state of high medical inflation. As a result, investors looking to protect their wealth against such a bad state would bid up the prices of these assets and consequently reduce returns to these assets. Thus one would predict that a high covariance between returns and medical inflation shocks would lead to lower expected returns. In other

words, we anticipate the medical inflation factor we have constructed should price negatively in equilibrium.

To determine if this unexpected result occurs consistently over time, we now subdivide the period of study into two sub-periods. The first period runs from January 1967 to December 1984; the second period from January 1985 to August 2009. Given the 60-month beta formation period at the beginning of our sample, these sub-periods contain 156 and 296 months' of return data, respectively. The rationale for subdividing the entire period at this date comes from Figure 1. The mid-1980s appears to be the time when medical inflation begins diverging from the other components of medical inflation and represents a reasonable basis for partitioning the sample.[11]

Table 8, Panel D contains the results of the subdivided sample in columns 3 and 4 for the specification 6 in Table 8, Panel A. For our basic specifications, although medical inflation surprises are priced positively across the entire sample period, this result only occurs because of their positive pricing in the early sub-period. In the more recent period, medical shocks price negatively and significantly, as we would predict. Additionally, while expected medical inflation prices (positively) in the earlier period, it fails to price in the latter period. Unfortunately the positively-priced medical inflation result in the early period remains a mystery despite multiple robustness tests and explorations, as we describe later.

[11] The pattern described in the following sub-period results also generally holds when we arbitrarily subdivide the sample into its 4 decades (1970s, 80s, 90s, and 2000s).

Two-pass method with other factors

We now augment the CRR (1986) model to include medical inflation as a potential source of priced risk. Like these authors, we leave the first-pass results untabulated, recognizing the challenge for our relatively smooth macroeconomic series to explain highly volatile security returns at a level with any meaningful significance. Instead, Table 9, Panel A presents the second-pass results from the CRR (1986) baseline and four model permutations.

The first column represents the basic CRR (1986) model results. The default risk premium (DEF) is priced, and the industrial production measure (INDPRO), while close, does not price at conventional statistical levels. Notably, our definition for TERM differs slightly from CRR, who use the one-month Treasury bill versus the three-month Treasury bill. While we are unable to replicate perfectly the CRR (1986) results essentially because we could not duplicate all of their data (e.g., they used 20 size portfolios versus the three, five, and ten currently available via Ken French's Data Library), our results for overlapping sub-periods align qualitatively. Model specifications that include medical inflation's expected and unexpected medical inflation, shown in column 2, indicate that unexpected medical inflation is priced at conventional statistical levels.

Comparable to CRR (1986), specifications 3 and 5 (columns 4 and 6) control for the market's influence by including the value-weighted market return premium (MKTRF) as a priced factor candidate. Once again, medical inflation surprises are priced (specification 3), and when we aggregate both expected and unexpected medical inflation, it prices significantly (specification 5). The market prices significantly (negative) in both specifications, and specification 4 shows that the aggregated medical

inflation factor is insensitive to the market's inclusion since it prices significantly absent the market's effects. Additionally, unexpected aggregate inflation prices in the specification (3) that controls for the excess market return. Overall, accounting for medical inflation in the CRR (1986) analysis strengthens the evidence that market participants demand return premia for exposure to medical inflation.

Again, while the medical inflation surprises price in equilibrium across the entire sample, the positive risk price is unexpected. As with the earlier analysis, we present the subdivided sample results in Table 9, Panel B. Since both specifications 2 and 3 from Table 9, Panel A are of interest, we conduct sub-sample analysis for both specifications in Table 9, Panel B. The results once again clearly indicate the positively-priced medical inflation factor for the entire period results from the strongly positive values during the pre-1984, or pre-divergence, phase. Medical inflation in both specifications prices negatively for the more recent time period. Also, in support of CRR (1986), both the DEF and TERM factors price in more recent times. Thus it appears again that the price of medical inflation as a source of risk has a time-dependent sign.

The next step in this analysis stems from the macroeconomic factor work presented in Flannery and Protopapadakis (2002). By investigating the returns to surprises in 17 macroeconomic series, these authors identify multiple novel series that appear to explain returns and thus could serve as candidates for priced risk factors. Health care, or medical inflation, is not one of the series they explicitly investigate, so our evidence about its pricing is new. Further, a positive externality of our efforts to price only the medical inflation macroeconomic factor is to extend their work by

"investigat[ing] whether investors earn excess returns for bearing the risks associated with any of [their] factor candidates."

Table 10, Panel A depicts the results using a subset of those macroeconomic variables deemed relevant by Flannery and Protopapadakis (2002). A few caveats are in order. First and foremost, we do not have the daily "surprise" data for each macroeconomic series that Flannery and Protopapadakis (2002) have available for their study. We have used only publicly-available information for our time series. Additionally, we have incorporated neither Unemployment nor Balance of Trade data. We have not located monthly values for the former variable at this time. The latter exhibits somewhat odd behavior across our period of study. While initially positive, it began a trend of decline around 1980, interrupted by a brief uptick in the late 1980s.

Due to these caveats, our analysis certainly has room for extension. For now, Table 10, Panel A presents evidence that even accounting for those candidate factors presented by Flannery and Protopapadakis (2002), medical inflation, both expected and unexpected, hold their own as priced macroeconomic risk factors across the entire time period. This general result holds across a variety of model specifications, and their economic relevance remains at approximately the same levels as those shown in prior tables. The risk premium is on the order of 0.04 to 0.06 percent per month, or approximately 48 to 72 basis points per year, for a one-unit-change in medical inflation beta.

Since a positively-priced medical inflation factor again emerges, we again conduct the sub-period analysis. As seen in earlier results, Table 10, Panel B indicates that medical inflation prices negatively, as expected, over the last 25 years. The positive

loading for the entire period is driven strictly by the highly-positive pricing during the period when medical inflation and other inflation components exhibited similar trends in their levels (see Figure 1).

The next, and final, analysis involves augmenting three model specifications based on the well-known Fama-French factors with medical inflation. Table 11, Panel A depicts the results on these second-pass regressions. Specifications 1, 4, and 7 (columns 2, 5, and 8) are the baseline specifications for a 3-factor, 5-factor, and 6-factor (i.e., 5-factor plus Momentum) analysis. Each respective subsequent specification (i.e., 2, 5, and 8) includes expected and unexpected medical inflation. The final specifications in each progression, 3, 6, and 9, replace disaggregated medical inflation with the composite value.

Regarding our variables of interest, contrary to our prior results, in no case is unexpected medical inflation priced when we incorporate it across the entire period. Furthermore, the composite medical inflation value is not priced in these specifications. Expected medical inflation is positively priced, albeit at a substantially lower economic value than we have seen in the prior tables. These results clearly do not support our hypothesis, per se, and as before, it is concerning that expected medical inflation carries some return premia here. As for the other factors, MKTRF (negative) and HML (positive) price in all specifications, TERM (positive) prices in all specifications save one, and MOM (negative) fails to price. SMB (positive) never prices, and DEF (negative) only prices at conventional levels in the final specification.

Once again, the results support our hypothesis when we subdivide the sample. Table 11, Panel B summarizes the subdivided second-pass of the final specification from

Table 11, Panel A, which includes all factors. While medical inflation surprise does not price across the entire period, the early sub-period again drives this insignificant result. In the more recent sub-period, medical inflation surprises price negatively, consistent with the results in our prior specifications. Additionally, the level of concern diminishes about expected medical inflation pricing across the entire time period. The subdivided results indicate expected medical inflation fails to price in the last 25 years. Finally, in more recent times, these data indicate MKTRF (negative), HML (positive), DEF (negative), and TERM (positive) all price significantly.

In an attempt to explain the counterintuitive finding that medical inflation prices positively from 1972 to 1984, we consider a couple possibilities. Given the Jensen, Mercer, and Johnson (1996) finding regarding the relationship between asset returns and the Federal Reserve's monetary policy stance, we posit that perhaps medical inflation pricing is conditioned upon the same monetary policy phenomenon. We divide the sample into contractionary and expansionary monetary policy periods according to the method described in Jensen, Mercer, and Johnson (1996), using their data augmented with data from the *Federal Reserve Statistical Release H.15, Selected Interest Rates* for more recent months. We then explore medical inflation pricing using two methods. In the first method, we simply test the means of medical inflation factor prices (i.e., λ from equation (6)) for any difference across the two monetary policy environments. While the evidence is not statistically convincing, perhaps this area is one for further future exploration since we find contractionary periods tend to load higher than expansionary periods with p-values ranging from 0.110 to 0.436 depending on the specification (results not tabulated).

In the next method, we test for a time-series difference in the relationship between asset returns and medical inflation surprise by interacting the medical inflation surprise with an indicator variable for whether each month occurs during a contractionary or expansionary timeframe. This method involves running the time series regressions of equation (5) for the whole period with an additional interaction term. Again, these untabulated results show no significant difference between the covariance between medical inflation shocks and asset returns associated with different monetary policy periods.

Robustness Test: Characteristics-Based Medical Care Factor

One possible criticism of the previous specification (see Table 11) is that there exists a mix of characteristics-based, zero investment factors such as SMB and HML alongside the macroeconomic medical inflation factor. Thus the next task we undertake is to form a zero investment portfolio medical factor and determine whether it is priced in equilibrium.

To create a medical high-beta minus low-beta (MedHML) factor, we form portfolios of securities based on their covariance with medical inflation shocks. Specifically, we pull from CRSP all stocks that have at least 60 months' of returns between January 1967 and December 2008, resulting in 16,093 firms. From these we draw a random sample of 3,000 firms. Beginning in January 1967, we perform time-series regressions of individual firm returns on medical inflation shocks, expected medical inflation, SMB, HML, DEF, TERM, and MOM for sixty months. We then order the firms based on the resulting beta associated with unexpected medical inflation and

use this ordering for the ensuing 12 months. We create quintiles of these stocks ordered by medical inflation news beta and calculate an equally-weighted monthly average of firm returns each quintile. Differencing the average returns of the high-beta quintile and low-beta quintile forms our MedHML factor. We roll the beta estimation period forward by 12 months and repeat the process. In the end we generate 444 MedHML returns for the period ranging from January 1972 to December 2008. Across the whole period there exists no statistical difference between the average returns of the high- and low-beta quintiles (i.e., MedHML is statistically no different than zero), which is not problematic (see Cochrane (2005)).

Given this MedHML series, we incorporate it as a factor and proceed with the Fama-MacBeth (1973) two-pass procedure using equations (5) and (6) to determine whether it is priced. We present the first-pass results for the entire period in Table 12, Panel A. Contrary to the less-than-impressive first-pass results in Table 8, Panel C, these results indicate that across the entire time period MedHML covaries significantly with the Fama-French 25 portfolio returns for 14 of the 25 portfolios at conventional significance levels. Additionally, the covariance is positive for small firms and then changes sign as firms grow in size. All else equal, small firms correlate better over time with medical inflation than do larger firms. We do not discern a pattern with the book-to-market measure.

The second-pass results are located in Table 12, Panel B. The result found in earlier specifications persists here. The medical inflation surprise factor—in this case MedHML—prices negatively in the most recent time period (see column 4). Because we lose an extra 60 months' of data moving from the previous specifications to this one, the

more recent sub-period is substantially larger than the earlier sub-period, and thus this negative pricing in the recent sub-period appears to dominate across the whole timeframe (column 2). Interpreted, this negative price on the MedHML zero investment portfolio indicates that as the difference between the medical inflation surprise betas (or returns) grows, expected returns decrease. In the end the market prices a risk factor formed by simultaneously taking a long (short) position in stocks exhibiting high (low) covariance with medical inflation surprises similarly to how it prices the macroeconomic medical inflation measure. Thus it appears that our finding of the market pricing the risk associated with health care costs is robust to creating a firm characteristics-based factor in addition to the macroeconomic factor analyzed earlier.

Discussion

While it appears at the aggregate level the risk to firms of health-care related costs are priced, one might wonder whether it would be more appropriate to partition the sample of firms into those who are large enough to self-insure versus those who purchase coverage from external agencies. Such an indicator variable would capture the incremental relationship between returns and self-insuring firms, but we believe the firm (i.e., portfolio) betas already capture these differences. Whether a firm self-insures or opts for an externally-managed plan, it will ultimately bear the cost of medical care for insured employees. Perhaps a delay in this cost recognition could occur if an external insurance company has to recoup an unexpected rise in costs (i.e., higher medical inflation) in a future period, but the firm will ultimately bear the expense. To the extent the market incorporates this information, it should be imputed into returns and allow the

firms' betas to capture the effects. Separately but related, it is not immediately clear that that by-firm self insurance data is available.

Another item of possible concern is whether medical inflation represents only the costs of medical care but is independent of the actual expenditures firms incur to purchase the care, which is a more accurate indicator of the risk posed by unexpected cost escalation in this area. As discussed, earlier, medical care inflation represents the cost index for a basket of medical care commodities and services. This component represents 6.39 percent of the aggregate inflation measure quantified by the Consumer Price Index (CPI). On the other hand, expenditures on medical care are generally tracked as a fraction of GDP. According to the Congressional Budget Office, spending on health care has grown from approximately 5 percent of GDP in 1960 to 17 percent today.[12] So while it is conceivable that costs increase but expenditures do not, which would argue against the use of medical inflation as a proxy for firm exposure to health care cost growth, the growth in medical care costs as a fraction of GDP indicates that expenditures are rising in addition to costs. Addtionally, results from the Kaiser Family Foundation 2009 Survey of Employer Health Benefits indicates that firms have increased their payment of medical benefits by 132 percent between 1999 and 2009. In the same period, the cost of medical care as measured by medical CPI has risen by 52 percent. Thus it appears using this cost-based measure of firms' exposure to medical care inflation could be more conservative than looking at firms' actual expenditures.

Perhaps the cost versus expenditure question loses some relevance when we consider the medical inflation surprise beta could account for it. Once again, the medical

[12] http://www.cbo.gov/ftpdocs/87xx/doc8758/MainText.3.1.shtml

inflation surprise beta captures the by-firm (i.e., portfolio) relationship between firm returns and medical inflation shocks and should account for the unique effect of price changes versus expenditure changes. For instance, if medical care costs (i.e., inflation) rise 10 percent but a firm implements a wellness program designed to decrease medical care needs for employees that exacts a 10 percent decrease in medical care services used, then these effects offset each other. Firm earnings experience no medical care induced shock, leading to no return difference due to this shock and exacting a zero beta (i.e., covariance) between the return and medical care shock. One might argue that firms who pay health insurance premiums are relatively-penalized since they pay these premiums regardless of medical care services used, but we assume the insurers act in an actuarially-neutral fashion and adjust premia in the subsequent time periods to reflect cost and expenditure changes. In other words, if there is a positive shock to medical inflation (cost) and health care usage (expenditures), then for an externally-insured firm the insurer will adjust future premiums to offset the unexpected loss. Conversely, these insurers will also adjust to offset an unexpected gain. This assumption makes the cost versus expenditure question moot, because ultimately firm earnings bear the brunt of any changes in medical care costs.

Finally, a clear contemporary policy question involves financing expanded health care in this country. Since the results of this study indicate investors in firms that are more exposed to medical inflation demand lower returns due to the hedging effect of such assets, a government intervention that reduces firms' risk of medical inflation would drive down prices of hedging assets and drive up prices of their risky counterparts. While

this wealth transfer from hedge-portfolio holders to those holding risky assets would occur, it is not apparent the government needs to correct it with a redistribution scheme.

Conclusion

Health care represents a major component of the US economy. In the past quarter-century its costs have risen much faster than price in the balance of the economy as measured by the Consumer Price Index. Despite these escalating costs, firms have shown resilience in their commitment to provide medical care as an employee benefit. To the extent firms are exposed to medical costs differently (i.e., more or less employees, better or worse health care plans, more or less leverage when negotiating rates with providers), their ultimate cash flows change as this component of their cost structure changes. To the extent the investors cannot diversify away this risk across firms, they will demand excess returns for bearing the risk of escalating medical expenses that firms evidently will not or cannot trim.

This study is an attempt to determine whether the market does indeed consider medical care costs a source of undiversifiable and hence priced risk. By separating the medical inflation component from the other basket of goods that composes aggregate inflation, one can generate a macroeconomic factor to test this question. Looking at monthly returns for the time period between January 1967 and August 2009, we lean on earlier factor models, specifically those generated by CRR (1986) and Fama and French (1993) as a baseline. Additionally, we incorporate the novel findings regarding macroeconomic factors from Flannery and Protopapadakis (2002). We augment these models to include an expected and unexpected medical inflation component, which we

generate based on Fama and Gibbons (1982) and Ansley (1980). At the top-level our findings generally support the contention that (unexpected) medical inflation does represent a priced risk factor, particularly in the last 25 years. Work still needs to be done for the earlier period of this study, 1967 to 1984, to determine why medical inflation surprises price in the opposite direction as one would anticipate.

Given these findings that suggest medical inflation surprises are priced in the market recently, they are by definition non-diversifiable. Since many large entities are liable for current and future medical care costs and must decide where to invest today to offset these future liabilities, our results indicate these entities cannot simply invest in the market and expect to fully fund health care expenses. Furthermore, Jennings, Fraser, and Payne (2009) highlight that more targeted and seemingly natural hedging investments such as health care mutual funds are not effective instruments to offset medical inflation. Faced with non-diversifiable medical care cost risk that is not naturally hedged, future work could determine what investable assets would serve as a mechanism to best hedge the risks associated with unanticipated health care cost changes.

References

Ahn, Seung C., Christopher Gadarowski, and M. Fabricio Perez, 2009, Effects of beta distribution and persistent factors on the two-pass cross-sectional regression, Working Paper from Financial Management Conference.

Ansley, Craig F., 1980, Signal extraction in finite series and the estimation of stochastic regression coefficients, Proceedings of the American Statistical Association (Business and Economic Statistics Section).

Campbell, John Y., Andrew W. Lo, and A. Craig Mackinlay, 1996, The econometrics of financial markets (Princeton University Press, NJ).

Carhart, Mark M., 1995b, Survivor bias and mutual fund performance, Working paper, School of Business Administration, University of Southern California, Los Angeles, CA.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383-403.

Christoffersen, Peter, Eric Ghysels, and Norman R. Swanson, 2001, Let's get "real" about using economic data, *Journal of Empirical Finance* 9, 343-60.

Cochrane, John H., 2005, Asset pricing (Princeton University Press, NJ).

Fama, Eugene F., ad James MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-36.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Michael R. Gibbons, 1982, Inflation, real returns, and capital investment, *Journal of Monetary Economics* 9, 297-323.

Fisher, Irving, 1930, The theory of interest (New York) reprinted in 1965 (A.M. Kelley, Clifton, NJ).

Flannery, Mark J. and Aris A. Protopapadakis, 2002, Macroeconomic factors do influence aggregate stock returns, *Review of Financial Studies* 15, 751-82.

Gibbons, M., S. Ross, and J. Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121-1152.

Hamilton, James D., 1994a, Time series analysis (Princeton University Press, NJ).

Himmelstein, David U., Deborah Thorne, Elizabeth Warren, and Steffie Woolhandler, 2009, Medical bankruptcy in the United States, 2007: Results of a national study, *American Journal of Medicine* 122, 741-46.

Hong, H, Torous, W, and R Valkanov, 2007, Do industries lead stock markets? *Journal of Financial Economics* 83, 367-96.

Jegadeesh, Narasimham, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jennings, William W., Steven Fraser, and Brian C. Payne, 2009, Do health care investments hedge health care liabilities? *Journal of Investing* 18, 69-74.

Jensen, Gerald R., Jeffrey M. Mercer, and Robert R. Johnson, 1996, Business conditions, monetary policy, and expected security returns, *Journal of Financial Economics* 40, 213-237.

Lamont, Owen, 2001, Economic tracking portfolios, *Journal of Econometrics* 105, 161-84.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13-37.

Pontiff, Jeffrey, and Lawrence D. Schall, 1998, Book-to-market ratios as predictors of market returns, *Journal of Finance* 49, 141-160.

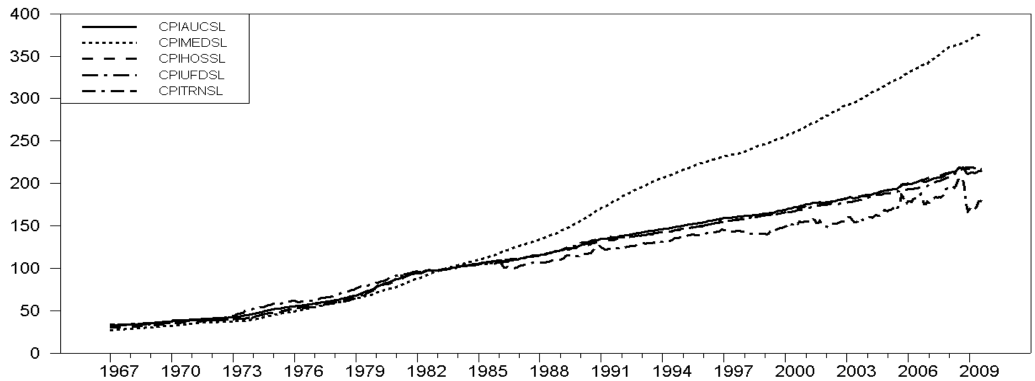
Ross, Stephen A., 1976, The arbitrage theory of capital asset pricing, *Journal of Economic Theory* 13, 341-60.

Sharpe, William F., 1964, Capital asset prices: a theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-42.

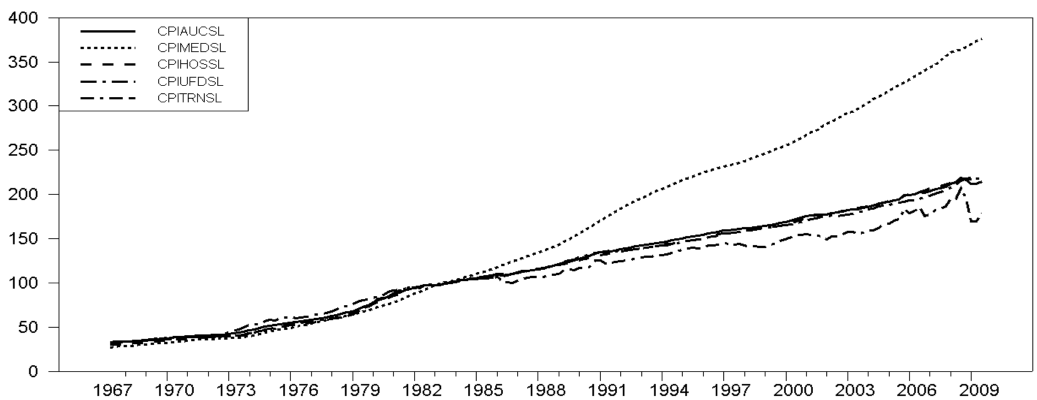
Appendix A
Figures

Figure 1

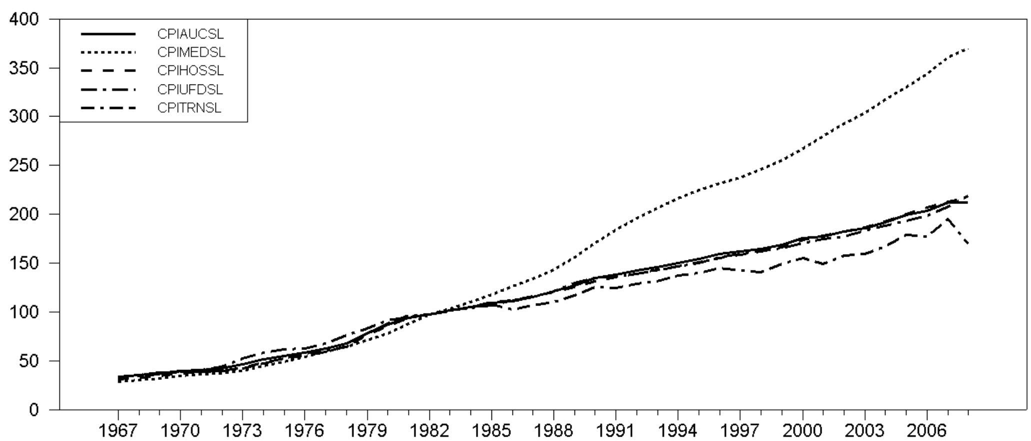
Panel A: Monthly Consumer Price Index (CPI) Levels



Panel B: Quarterly CPI Levels



Panel C: Annual CPI Levels



CPIAUCSL: Aggregate Inflation
CPIMEDSL: Medical Component
CPIHOSSL: Housing Component
CPIUFDSL: Food Component
CPITRNSL: Transportation Component

Figure 2
Monthly Joint Distributions of Inflation Components, Sorted into Quartiles

CPIMEDMO vs. CPIAUCMO

	1	2	3	4
1	**54**	34	22	17
2	34	**45**	28	15
3	24	29	**43**	31
4	13	16	33	**64**

CPIMEDMO vs. CPIHOSMO

	1	2	3	4
1	**42**	**52**	23	10
2	**39**	**38**	37	8
3	23	28	37	**39**
4	20	9	26	**71**

CPIMEDMO vs. CPIUFDMO

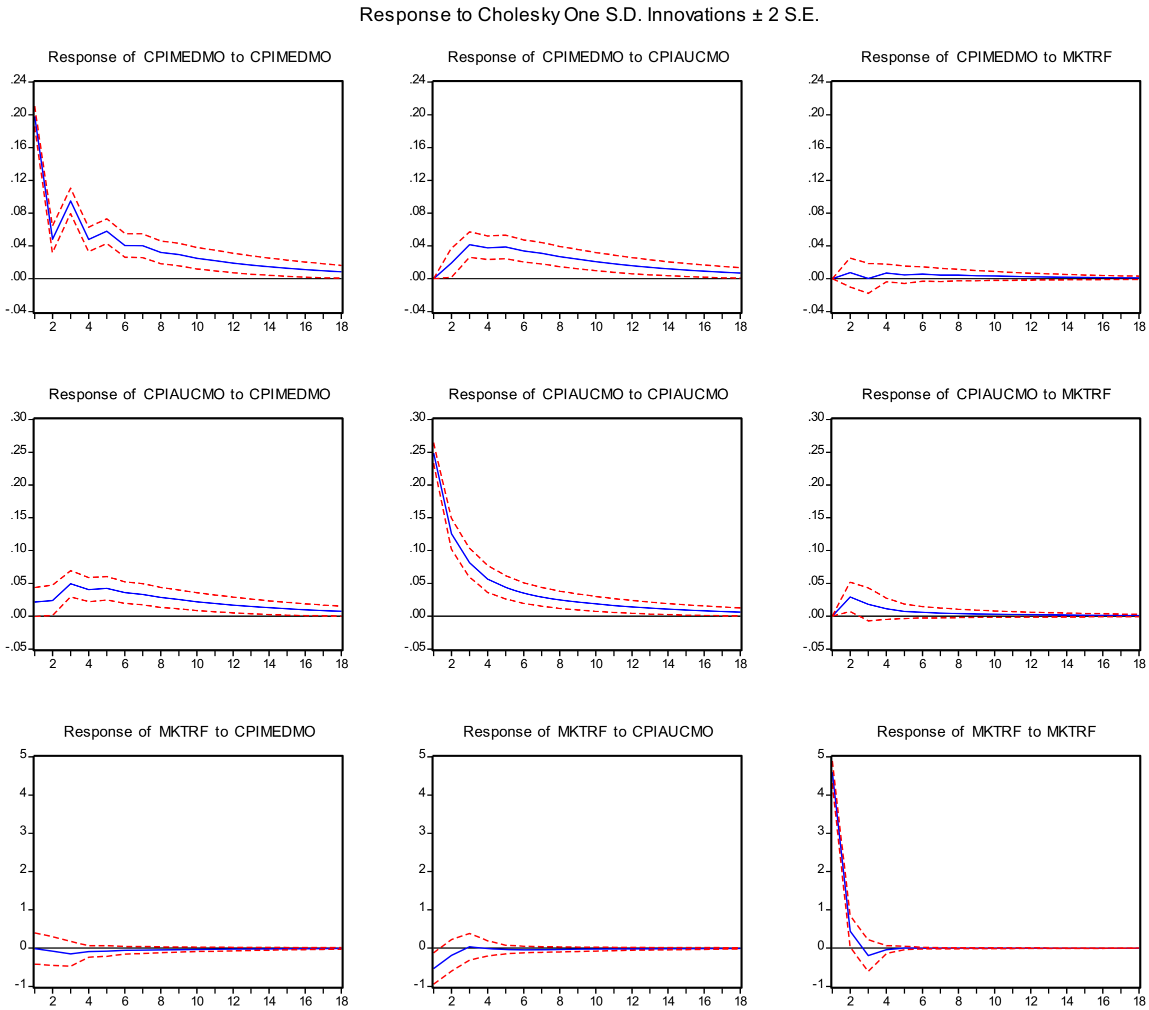
	1	2	3	4
1	32	**40**	30	25
2	33	**44**	33	12
3	33	26	32	36
4	25	17	31	**53**

CPIMEDMO vs. CPITRNMO

	1	2	3	4
1	**42**	35	22	28
2	37	29	23	33
3	23	**38**	**45**	21
4	25	21	34	**46**

These 4x4 grids represent the results of a 1000-iteration bootstrapping simulation in which the first time series, monthly medical inflation (CPIMEDMO), values are placed into quartiles. Next, the values for the time series listed second (e.g., CPIAUCMO in the first example) are also placed into quartiles. The numbers in each quartile intersection represents the number of times the quartile values match for the period January 1967 to August 2009. For example, monthly medical inflation (CPIMEDMO) and monthly aggregate inflation (CPIAUCMO) are both in their lowest quartile range (i.e., 1,1) 54 times during the period of study. To determine whether this value is statistically higher (or lower) than it would be if the series were independent, we randomly reorder the second time series 1000 times. Generally, at the 10 percent level, the values for all quartile combinations fall between 27 and 32 for these random pairings. The bold font (underlined font) and shaded cells represent quartile intersections that are statistically higher (lower) than these 10 percent cutoffs. Variables are defined in Figure 1.

Figure 3
Impulse Response Functions for Three-Variable Vector Autoregression (VAR) Model



These results depict the 18-month response of medical inflation (*CPIMEDMO*), aggregate inflation (*CPIAUCMO*), and the market's return excess of the risk free rate (*MKTRF*) in the following VAR model to a one-standard deviation shock to itself and the other variables in the system for the period January 1967 to August 2009.

$$CPIMEDMO_t = \alpha_0 + \alpha_{1,i}CPIMEDMO_{t-i} + \alpha_{2,i}CPIAUCMO_{t-i} + \alpha_{3,i}MKTRF_{t-i} + u_t$$
$$CPIAUCMO_t = \beta_0 + \beta_{1,i}CPIMEDMO_{t-i} + \beta_{2,i}CPIAUCMO_{t-i} + \beta_{3,i}MKTRF_{t-i} + v_t$$
$$MKTRF_t = \delta_0 + \delta_{1,i}CPIMEDMO_{t-i} + \delta_{2,i}CPIAUCMO_{t-i} + \delta_{3,i}MKTRF_{t-i} + w_t$$

Note i = 1, 2 for a two-lag model using the Schwarz criterion for lag length. Implicit causal ordering is shown above (CPIMEDMO, CPIAUCMO, and MKTRF), with the results insensitive to changes in this ordering. These response functions use the Cholesky decomposition to orthogonalize the residuals, and dashed lines represent the two-standard-deviation confidence bands.

Figure 4
Monthly Joint Distributions of Potential Risk Factors, Sorted into Quartiles

CPIMEDMO vs. SMB

	1	**2**	**3**	**4**
1	**42**	28	24	33
2	30	31	30	31
3	32	37	30	28
4	23	31	**39**	33

CPIMEDMO vs. HML

	1	**2**	**3**	**4**
1	34	30	30	33
2	29	31	30	32
3	31	34	27	35
4	30	31	**38**	27

CPIMEDMO vs. MOM

	1	**2**	**3**	**4**
1	31	20	36	**40**
2	36	32	27	27
3	32	37	34	24
4	26	36	28	36

CPIMEDMO vs. DEF

	1	**2**	**3**	**4**
1	27	35	22	**43**
2	29	33	37	23
3	28	26	**49**	24
4	34	35	19	**38**

CPIMEDMO vs. TERM

	1	**2**	**3**	**4**
1	30	**48**	32	17
2	29	23	27	**43**
3	25	19	**42**	**41**
4	**40**	34	25	27

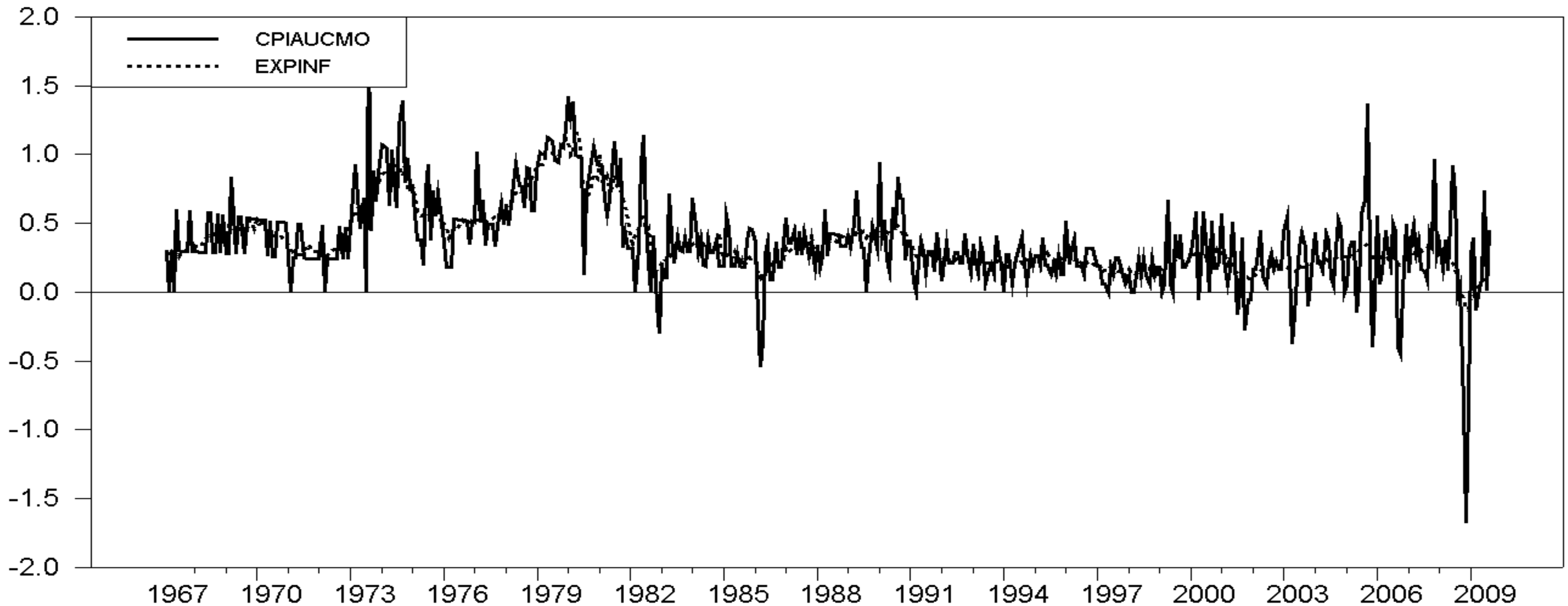
CPIAUCMO vs. TERM

	1	**2**	**3**	**4**
1	32	28	26	**39**
2	20	33	32	**39**
3	16	29	**43**	**38**
4	**56**	34	25	12

These 4x4 grids represent the results of a 1000-iteration bootstrapping simulation in which the first time series, monthly medical inflation (CPIMEDMO), values are placed into quartiles. Next, the values for the time series listed second (e.g., SMB in the first example) are also placed into quartiles. The numbers in each quartile intersection represents the number of times the quartile values match for the period January 1967 to August 2009. For example, monthly medical inflation (CPIMEDMO) and the Fama-French (1992) SMB factor are both in their lowest quartile range (i.e., 1,1) 42 times during the period of study. To determine whether this value is statistically higher (or lower) than it would be if the series were independent, we randomly reorder the second time series 1000 times. Generally, at the 10 percent level, the values for all quartile combinations fall between 27 and 32 for these random pairings. The pink (green) shading represent quartile intersections that are statistically higher (lower) than these 10 percent cutoffs. Variables include the Fama and French (1993) factors SMB, HML, DEF, and TERM; the Carhart (1997) momentum (MOM) factor; and aggregate inflation (CPIAUCMO).

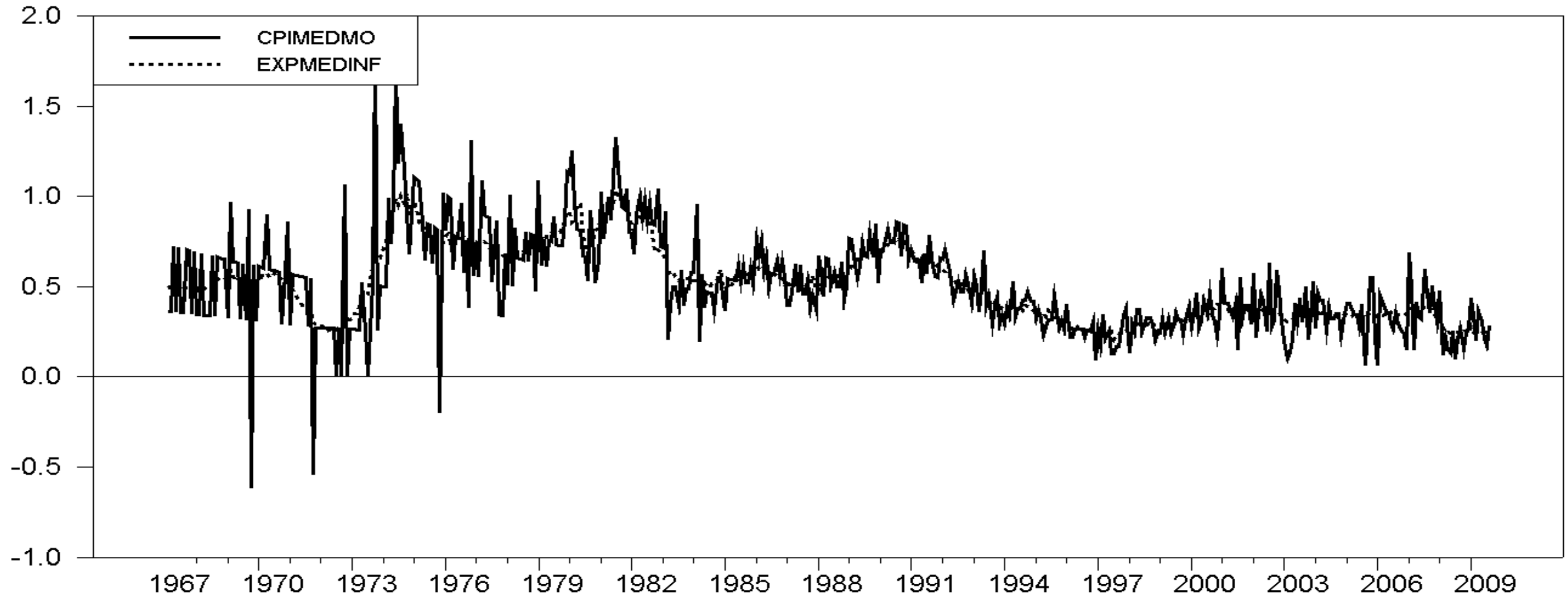
Figure 5

Plot of Actual (CPIAUCMO) vs. Expected (EXMEDINF) Aggregate Inflation using Kalman Filter Model (January 1967-August 2009)



Time series plot of actual monthly aggregate inflation (CPIAUCMO) versus the expected monthly aggregate inflation (EXPINF). The expected monthly inflation series is calculated based on the Fisher (1930) relationship between inflation and interest rates according to a Kalman Filter methodology developed by Ansley (1980) as described in Fama and Gibbons (1989). This procedure permits the constant within a regression model to change dynamically based on past data trends in an effort to discern the difference between the true signal and "noise" associated with the signal. In this analysis the expected inflation component represents the signal, and the unexpected component is the "noise."

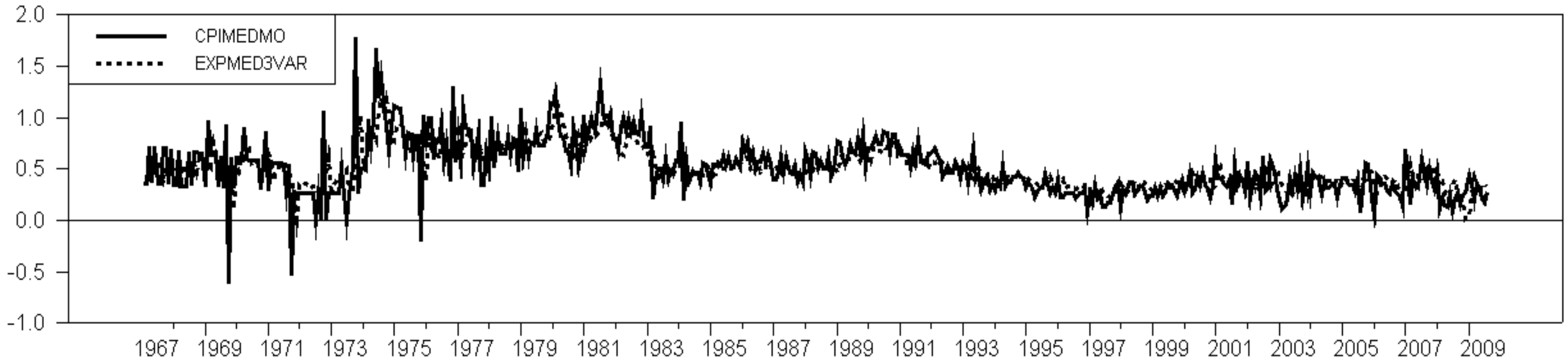
Figure 6
Plot of Actual (CPIMEDMO) vs. Expected (EXMEDINF) Medical Inflation using Kalman Filter Model (January 1967-August 2009)



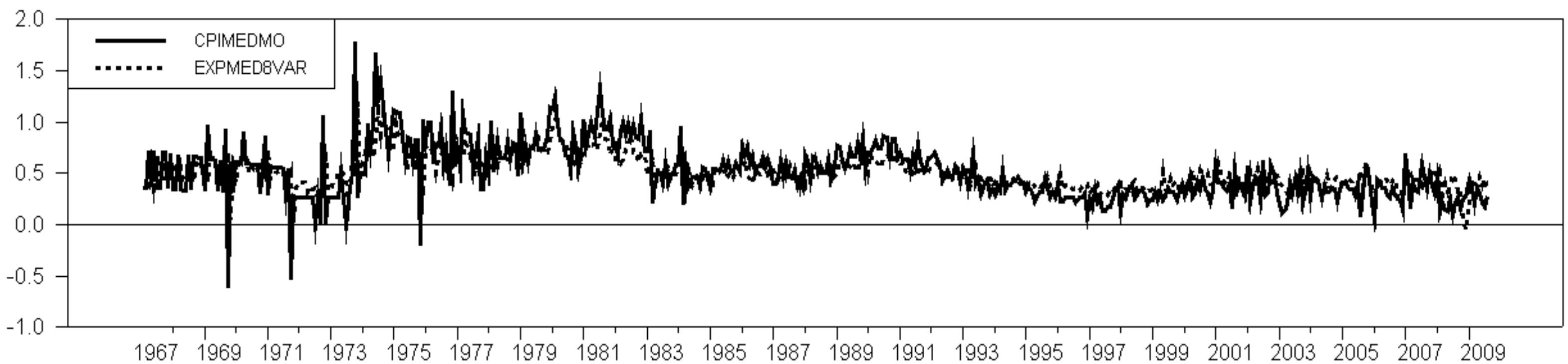
Time series plot of actual monthly medical inflation (CPIMEDMO) versus the expected monthly medical inflation (EXPMEDINF). The expected monthly inflation series is calculated based on the Fisher (1930) relationship between inflation and interest rates according to a Kalman Filter methodology developed by Ansley (1980) as described in Fama and Gibbons (1989). This procedure permits the constant within a regression model to change dynamically based on past data trends in an effort to discern the difference between the true signal and "noise" associated with the signal. In this analysis the expected inflation component represents the signal, and the unexpected component is the "noise."

Figure 7

Panel A: Acutal Medical Inflation and Expected Medical Inflation from a Three-Variable Vector Autoregression Model (January 1967-August 2009)



Panel B: Acutal Medical Inflation and Expected Medical Inflation from an Eight-Variable Vector Autoregression Model (January 1967-August 2009)



Time series plots of actual monthly medical inflation (CPIMEDMO) and two different measures of the expected component of monthly medical inflation. EXPMED3VAR is the estimated value of CPIMEDMO from a twice-lagged three-variable vector autoregression (VAR) including

monthly medical inflation, aggregate inflation, and the excess return on the value-weighted market above the risk-free rate of a one-month Treasury bill (MKTRF). Pearson correlation between these series is 0.688. EXPMED8VAR includes the aforementioned three variables augmented with (once-lagged) SMB, HML, DEF, TERM, and MOM factors. Pearson correlation between these series is 0.590.

Appendix B
Tables

Table 1

Panel A: Monthly Covariance/Correlation Table

	CPIMEDMO	CPIAUCMO	CPIHOSMO	CPIUFDMO	CPITRNMO
CPIMEDMO	0.073	0.405	0.452	0.109	0.141
CPIAUCMO	0.036	0.107	0.741	0.525	0.736
CPIHOSMO	0.041	0.081	0.112	0.302	0.296
CPIUFDMO	0.014	0.082	0.048	0.227	0.095
CPITRNMO	0.040	0.253	0.104	0.047	1.103

Panel B: Quarterly Covariance/Correlation Table

	CPIMEDQ	CPIAUCQ	CPIHOSQ	CPIUFDQ	CPITRNQ
CPIMEDQ	0.462	0.580	0.632	0.261	0.275
CPIAUCQ	0.327	0.690	0.878	0.628	0.768
CPIHOSQ	0.372	0.631	0.748	0.499	0.484
CPIUFDQ	0.182	0.537	0.444	1.057	0.218
CPITRNQ	0.406	1.385	0.908	0.487	4.713

Panel C: Annual Covariance/Correlation Table

	CPIMEDA	CPIAUCA	CPIHOSA	CPIUFDA	CPITRNA
CPIMEDA	6.244	0.722	0.721	0.337	0.563
CPIAUCA	5.108	8.010	0.966	0.727	0.817
CPIHOSA	5.491	8.323	9.276	0.662	0.729
CPIUFDA	2.774	6.785	6.642	10.863	0.341
CPITRNA	7.458	12.243	11.769	5.952	28.060

Table 1 shows the Pearson correlations among inflation variables at various sampling frequencies in the upper triangles. Covariances are shown on the diagonal and lower triangles. Variable definitions follow.

CPIMEDxx: Medical Component
CPIAUCxx: Aggregate Inflation
CPIHOSxx: Housing Component
CPIUFDxx: Food Component
CPITRNxx: Transportation Component

Table 2
Vector Autoregression (VAR) Estimates
(January 1967-August 2009)

Included observations: 509 after adjustments			
Standard errors in ( ) & t-statistics in [ ]			
	CPIMEDMO	CPIAUCMO	MKTRF
CPIMEDMO(t-1)	0.235	0.065	-0.351
	(0.040)	(0.051)	(0.944)
	[5.802]	[1.273]	[-0.372]
CPIMEDMO(t-2)	0.401	0.166	-0.619
	(0.040)	(0.050)	(0.931)
	[10.060]	[3.298]	[-0.665]
CPIAUCMO(t-1)	0.0809	0.518	-0.556
	(0.036)	(0.045)	(0.830)
	[2.276]	[11.565]	[-0.671]
CPIAUCMO(t-2)	0.107	0.065	0.410
	(0.036)	(0.046)	(0.843)
	[2.965]	[1.429]	[0.487]
MKTRF(t-1)	0.002	0.006	0.096
	(0.002)	(0.002)	(0.045)
	[0.841]	[2.621]	[2.142]
MKTRF(t-2)	-0.001	0.000	-0.048
	(0.002)	(0.002)	(0.045)
	[-0.493]	[-0.041]	[-1.056]
Constant	0.117	0.033	0.920
	(0.021)	(0.027)	(0.492)
	[5.563]	[1.240]	[1.869]
R-squared	0.473	0.425	0.016
Adj. R-squared	0.467	0.418	0.004

Table 2 depicts the VAR parameters for the period January 1967 to August 2009 for the following model, which includes medical inflation (*CPIMEDMO*), aggregate inflation (*CPIAUCMO*), and the market's return excess of the risk free rate (*MKTRF*).

$$CPIMEDMO_t = \alpha_0 + \alpha_{1,i}CPIMEDMO_{t-i} + \alpha_{2,i}CPIAUCMO_{t-i} + \alpha_{3,i}MKTRF_{t-i} + u_t$$
$$CPIAUCMO_t = \beta_0 + \beta_{1,i}CPIMEDMO_{t-i} + \beta_{2,i}CPIAUCMO_{t-i} + \beta_{3,i}MKTRF_{t-i} + v_t$$
$$MKTRF_t = \delta_0 + \delta_{1,i}CPIMEDMO_{t-i} + \delta_{2,i}CPIAUCMO_{t-i} + \delta_{3,i}MKTRF_{t-i} + w_t$$

Note i = 1, 2 for a two-lag model using the Schwarz criterion for lag length.

Table 3
Variance Decomposition
(January 1967-August 2009)

Variance Decomposition of CPIMEDMO:				
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**
1	0.20	100.00	0.00	0.00
2	0.21	98.98	0.88	0.13
3	0.23	95.92	3.97	0.10
4	0.24	93.59	6.23	0.18
5	0.25	91.62	8.18	0.20
6	0.25	90.16	9.60	0.25
7	0.26	89.08	10.66	0.27
8	0.26	88.28	11.44	0.29
9	0.26	87.69	12.01	0.30
10	0.27	87.25	12.44	0.31
11	0.27	86.92	12.76	0.32
12	0.27	86.68	13.00	0.32
13	0.27	86.50	13.17	0.33
14	0.27	86.36	13.31	0.33
15	0.27	86.25	13.41	0.34
16	0.27	86.17	13.49	0.34
17	0.27	86.11	13.55	0.34
18	0.27	86.07	13.59	0.34
Variance Decomposition of CPIAUCMO:				
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**
1	0.25	0.74	99.26	0.00
2	0.28	1.30	97.63	1.07
3	0.30	3.89	94.79	1.32
4	0.31	5.42	93.20	1.38
5	0.31	7.05	91.57	1.38
6	0.32	8.15	90.47	1.38
7	0.32	9.07	89.55	1.38
8	0.32	9.73	88.90	1.37
9	0.32	10.24	88.39	1.37
10	0.33	10.62	88.02	1.37
11	0.33	10.91	87.73	1.36
12	0.33	11.12	87.51	1.36
13	0.33	11.29	87.35	1.36
14	0.33	11.41	87.23	1.36
15	0.33	11.51	87.13	1.36

16	0.33	11.58	87.06	1.36
17	0.33	11.63	87.01	1.36
18	0.33	11.67	86.97	1.36
Variance Decomposition of MKTRF:				
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**
1	4.63	0.00	1.34	98.66
2	4.65	0.03	1.49	98.48
3	4.66	0.14	1.49	98.37
4	4.66	0.18	1.49	98.33
5	4.66	0.21	1.50	98.30
6	4.66	0.22	1.50	98.27
7	4.66	0.24	1.51	98.25
8	4.66	0.25	1.52	98.24
9	4.66	0.25	1.52	98.23
10	4.66	0.26	1.53	98.22
11	4.66	0.26	1.53	98.21
12	4.66	0.27	1.53	98.20
13	4.66	0.27	1.53	98.20
14	4.66	0.27	1.53	98.20
15	4.66	0.27	1.53	98.20
16	4.66	0.27	1.53	98.19
17	4.66	0.27	1.53	98.19
18	4.66	0.27	1.54	98.19
Cholesky Ordering: CPIMEDMO CPIAUCMO MKTRF				

Table 3 depicts the variance decomposition for the following VAR system for the period January 1967 to August 2009.

$$CPIMEDMO_t = \alpha_0 + \alpha_{1,i}CPIMEDMO_{t-i} + \alpha_{2,i}CPIAUCMO_{t-i} + \alpha_{3,i}MKTRF_{t-i} + u_t$$
$$CPIAUCMO_t = \beta_0 + \beta_{1,i}CPIMEDMO_{t-i} + \beta_{2,i}CPIAUCMO_{t-i} + \beta_{3,i}MKTRF_{t-i} + v_t$$
$$MKTRF_t = \delta_0 + \delta_{1,i}CPIMEDMO_{t-i} + \delta_{2,i}CPIAUCMO_{t-i} + \delta_{3,i}MKTRF_{t-i} + w_t$$

Variables include medical inflation (*CPIMEDMO*), aggregate inflation (*CPIAUCMO*), and the market's return excess of the risk free rate (*MKTRF*). Note i = 1, 2 for a two-lag model using the Schwarz criterion for lag length.

Table 4

Panel A: Monthly Covariance/Correlation Table

	CPIMEDMO	MKTRF	SMB	HML	MOM	DEF	TERM
CPIMEDMO	0.073	-0.039	0.031	0.033	0.030	-0.081	-0.080
MKTRF	-0.049	21.405	0.298	-0.340	-0.142	0.051	0.018
SMB	0.027	4.427	10.342	-0.255	-0.027	0.070	0.061
HML	0.027	-4.771	-2.487	9.193	-0.162	-0.042	-0.019
MOM	0.037	-2.953	-0.387	-2.207	20.147	-0.158	-0.024
DEF	-0.016	0.175	0.166	-0.094	-0.523	0.548	0.306
TERM	-0.027	0.105	0.247	-0.074	-0.137	0.287	1.607

Panel B: Quarterly Covariance/Correlation Table

	CPIMEDQ	MKTRFQ	SMBQ	HMLQ	MOMQ	DEFQ	TERMQ
CPIMEDQ	0.462	-0.067	0.039	0.060	0.066	-0.098	-0.091
MKTRFQ	-0.352	59.047	0.421	-0.278	-0.134	0.039	0.057
SMBQ	0.145	17.652	29.757	-0.249	-0.016	0.140	0.099
HMLQ	0.211	-11.133	-7.066	27.084	-0.164	-0.073	0.037
MOMQ	0.312	-7.155	-0.610	-5.903	48.026	-0.251	-0.081
DEFQ	-0.145	0.651	1.659	-0.828	-3.774	4.723	0.345
TERMQ	-0.224	1.577	1.947	0.692	-2.024	2.710	13.096

Panel C: Annual Covariance/Correlation Table

	CPIMEDA	MKTRFA	SMBA	HMLA	MOMA	DEFA	TERMA
CPIMEDA	6.244	-0.103	0.222	0.069	0.040	-0.083	-0.092
MKTRFA	-4.651	328.455	0.246	-0.272	-0.081	-0.189	0.185
SMBA	7.093	56.794	162.802	0.085	-0.262	0.168	0.293
HMLA	2.503	-71.086	15.697	208.432	-0.398	0.079	0.134
MOMA	1.401	-20.567	-46.742	-80.212	195.279	-0.042	-0.257
DEFA	-1.457	-24.137	15.135	8.041	-4.184	49.665	0.330
TERMA	-3.087	45.176	50.295	26.077	-48.338	31.242	180.672

Table 4 shows the Pearson correlation among various factors at various sampling frequencies in the upper triangles. Covariances are shown on the diagonal and lower triangles. Variable definitions follow.

CPIMEDxx: Medical Component of inflation
MKTRFxx: Value-weighted market return in excess of the risk-free rate
SMBxx: SMB factor as described by Fama and French (1993)
HMLxx: HML factor as described by Fama and French (1993)
MOMxx: Momentum factor as described by Carhart (1997)
DEFxx: Default risk premium as described by Chen, Roll, and Ross (CRR) (1986)
TERMxx: Term risk premium as described by CRR (1986)

Table 5
Vector Autoregression (VAR) Estimates
(January 1967-August 2009)

Included observations: 509 after adjustments								
Standard errors in ( ) & t-statistics in [ ]								
	CPIMEDMO	CPIAUCMO	MKTRF	SMB	HML	DEF	TERM	MOM
CPIMEDMO (t-1)	0.447	0.174	-0.630	0.212	0.446	0.037	0.195	0.719
	-0.040	-0.044	-0.831	-0.564	-0.537	-0.034	-0.084	-0.788
	[11.273]	[3.909]	[-0.758]	[0.375]	[0.831]	[1.080]	[2.321]	[0.912]
CPIAUCMO (t-1)	0.199	0.502	-0.219	0.262	0.557	-0.027	-0.051	-0.410
	-0.036	-0.040	-0.750	-0.509	-0.484	-0.031	-0.076	-0.711
	[5.560]	[12.530]	[-0.291]	[0.515]	[1.151]	[-0.858]	[-0.671]	[-0.577]
MKTRF(t-1)	0.002	0.004	0.068	0.158	0.067	-0.014	0.018	-0.165
	-0.002	-0.003	-0.050	-0.034	-0.032	-0.002	-0.005	-0.047
	[0.829]	[1.467]	[1.359]	[4.673]	[2.100]	[-7.009]	[3.571]	[-3.497]
SMB(t-1)	0.004	0.006	0.088	-0.023	0.019	-0.006	0.014	0.113
	-0.003	-0.004	-0.068	-0.046	-0.044	-0.003	-0.007	-0.064
	[1.148]	[1.782]	[1.293]	[-0.498]	[0.438]	[-2.010]	[1.972]	[1.758]
HML(t-1)	0.006	-0.003	-0.026	0.016	0.185	-0.007	0.027	-0.145
	-0.004	-0.004	-0.076	-0.051	-0.049	-0.003	-0.008	-0.072
	[1.573]	[-0.817]	[-0.343]	[0.316]	[3.800]	[-2.382]	[3.548]	[-2.028]
DEF(t-1)	0.009	-0.056	0.221	0.433	-0.181	0.973	0.171	-1.139
	-0.015	-0.016	-0.307	-0.208	-0.198	-0.013	-0.031	-0.291
	[0.632]	[-3.417]	[0.719]	[2.081]	[-0.915]	[76.957]	[5.531]	[-3.915]
TERM(t-1)	-0.002	-0.026	0.021	0.039	0.137	-0.009	0.888	0.105
	-0.008	-0.009	-0.174	-0.118	-0.113	-0.007	-0.018	-0.165
	[-0.240]	[-2.747]	[0.122]	[0.327]	[1.217]	[-1.187]	[50.462]	[0.636]
MOM(t-1)	0.000	-0.002	-0.004	-0.027	-0.023	0.007	-0.002	0.004
	-0.002	-0.003	-0.048	-0.033	-0.031	-0.002	-0.005	-0.046
	[0.090]	[-0.910]	[-0.077]	[-0.839]	[-0.732]	[3.428]	[-0.342]	[0.097]
Constant	0.191	0.252	0.276	-0.982	0.048	0.068	-0.261	2.760
	-0.040	-0.045	-0.839	-0.569	-0.542	-0.035	-0.085	-0.795
	[4.775]	[5.614]	[0.329]	[-1.726]	[0.088]	[1.969]	[-3.086]	[3.470]
R-squared	0.348	0.438	0.018	0.062	0.045	0.935	0.866	0.062
Adj. R-squared	0.338	0.429	0.002	0.047	0.030	0.934	0.864	0.047

Table 5 depicts the VAR parameters for the period January 1967 to August 2009 for the following model.

$$Z_t = \Gamma Z_{t-1} + u_t$$

Z_t is a (8 x 1) state vector that includes medical inflation (CPIMEDMO), aggregate inflation (CPIAUCMO), market excess return over the risk-free rate (MKTRF), SMB, HML, MOM, DEF, and TERM, Γ represents the (8 x 8) matrix of parameters, and u_t is the (8 x 1) vector of error terms for each respective variable in the state vector. Note this model uses one-lag based on the Schwarz criterion for lag length.

Table 6
Variance Decomposition
(January 1967-August 2009)

Variance Decomposition of CPIMEDMO:									
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**	**SMB**	**HML**	**DEF**	**TERM**	**MOM**
1	0.221	100.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.250	95.776	3.657	0.068	0.100	0.389	0.007	0.001	0.001
3	0.262	92.665	6.387	0.276	0.173	0.466	0.011	0.013	0.009
4	0.267	90.976	7.845	0.422	0.212	0.474	0.012	0.043	0.016
5	0.269	90.128	8.555	0.498	0.230	0.472	0.012	0.086	0.020
6	0.271	89.696	8.889	0.535	0.237	0.470	0.013	0.137	0.023
7	0.271	89.462	9.046	0.555	0.241	0.469	0.015	0.188	0.024
8	0.271	89.321	9.119	0.567	0.242	0.468	0.022	0.235	0.026
9	0.271	89.226	9.152	0.575	0.243	0.468	0.033	0.276	0.027
10	0.272	89.153	9.167	0.581	0.243	0.468	0.049	0.311	0.028
11	0.272	89.091	9.172	0.587	0.244	0.467	0.071	0.338	0.029
12	0.272	89.035	9.173	0.593	0.244	0.467	0.097	0.360	0.031
13	0.272	88.982	9.172	0.599	0.244	0.467	0.128	0.377	0.032
14	0.272	88.930	9.169	0.605	0.244	0.467	0.163	0.389	0.033
15	0.272	88.878	9.165	0.612	0.244	0.467	0.201	0.398	0.034
16	0.272	88.827	9.161	0.619	0.244	0.467	0.242	0.405	0.036
17	0.272	88.776	9.157	0.626	0.245	0.467	0.283	0.409	0.037
18	0.272	88.726	9.152	0.633	0.245	0.467	0.326	0.412	0.038
Variance Decomposition of CPIAUCMO:									
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**	**SMB**	**HML**	**DEF**	**TERM**	**MOM**
1	0.248	2.529	97.471	0.000	0.000	0.000	0.000	0.000	0.000
2	0.285	6.154	91.923	1.033	0.544	0.038	0.041	0.145	0.122
3	0.299	7.885	89.131	1.639	0.652	0.035	0.109	0.387	0.163
4	0.305	8.543	87.757	1.912	0.693	0.036	0.214	0.660	0.185
5	0.308	8.732	86.963	2.068	0.709	0.039	0.362	0.925	0.202
6	0.310	8.742	86.394	2.173	0.716	0.042	0.557	1.161	0.216
7	0.311	8.695	85.905	2.255	0.719	0.044	0.796	1.357	0.229
8	0.312	8.638	85.439	2.324	0.720	0.046	1.077	1.514	0.242
9	0.313	8.585	84.978	2.388	0.721	0.049	1.392	1.634	0.254
10	0.314	8.539	84.516	2.450	0.721	0.051	1.736	1.722	0.266
11	0.315	8.499	84.054	2.510	0.721	0.054	2.101	1.784	0.277
12	0.316	8.463	83.594	2.571	0.721	0.056	2.480	1.825	0.289
13	0.317	8.429	83.141	2.632	0.721	0.059	2.867	1.851	0.301
14	0.318	8.396	82.696	2.693	0.722	0.063	3.255	1.865	0.312

15	0.318	8.364	82.262	2.754	0.722	0.066	3.639	1.870	0.323
16	0.319	8.333	81.843	2.814	0.723	0.069	4.015	1.870	0.333
17	0.320	8.302	81.440	2.873	0.724	0.073	4.380	1.866	0.343
18	0.321	8.271	81.055	2.930	0.725	0.076	4.731	1.860	0.353
Variance Decomposition of MKTRF:									
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**	**SMB**	**HML**	**DEF**	**TERM**	**MOM**
1	4.631	0.013	1.399	98.588	0.000	0.000	0.000	0.000	0.000
18	4.670	0.150	1.488	97.797	0.354	0.025	0.176	0.003	0.007
Variance Decomposition of SMB:									
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**	**SMB**	**HML**	**DEF**	**TERM**	**MOM**
1	3.142	0.123	0.036	8.176	91.665	0.000	0.000	0.000	0.000
18	3.241	0.157	0.054	12.536	86.264	0.057	0.777	0.008	0.146
Variance Decomposition of HML:									
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**	**SMB**	**HML**	**DEF**	**TERM**	**MOM**
1	2.989	0.096	0.190	11.858	3.581	84.276	0.000	0.000	0.000
18	3.061	0.378	0.551	11.779	3.460	83.385	0.174	0.156	0.117
Variance Decomposition of DEF:									
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**	**SMB**	**HML**	**DEF**	**TERM**	**MOM**
1	0.191	0.081	1.864	0.036	0.281	0.415	97.323	0.000	0.000
18	0.682	0.656	1.121	14.014	1.131	0.894	79.235	0.940	2.008
Variance Decomposition of TERM:									
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**	**SMB**	**HML**	**DEF**	**TERM**	**MOM**
1	0.468	0.001	0.192	0.296	0.071	2.851	16.687	79.903	0.000
18	1.080	3.938	0.875	3.094	0.386	0.744	22.237	68.144	0.582
Variance Decomposition of MOM:									
Period	**S.E.**	**CPIMEDMO**	**CPIAUCMO**	**MKTRF**	**SMB**	**HML**	**DEF**	**TERM**	**MOM**
1	4.390	0.004	0.208	1.684	0.360	4.435	0.005	0.022	93.283
18	4.524	0.166	0.220	3.214	1.304	5.083	2.012	0.109	87.893
Cholesky Ordering: CPIMEDMO CPIAUCMO MKTRF SMB HML DEF TERM MOM									

Table 6 depicts the variance decomposition for the following VAR system for the period January 1967 to August 2009.

$$Z_t = \Gamma Z_{t-1} + u_t$$

Z_t is a (8 x 1) state vector that includes medical inflation (CPIMEDMO), aggregate inflation (CPIAUCMO), market excess return over the risk-free rate (MKTRF), SMB, HML, MOM, DEF, and TERM, Γ represents the (8 x 8) matrix of parameters, and u_t is the (8 x 1) vector of error terms for each respective variable in the state vector. Note this model uses one-lag based on the Schwarz criterion for lag length.

Table 7
Covariance/Correlation Table for Various Measures of Unexpected Medical Inflation and Other Possible Proxies
(January 1967-August 2009)

	UNEXPMEDKALMAN	UNEXPMED3VAR	UNEXPMED8VAR	UNEXPINF	CPIAUCMO	TERM	CPIMEDMO
UNEXPMEDKALMAN	0.027	0.889	0.853	0.003	0.009	-0.001	0.678
UNEXPMED3VAR	0.029	0.039	0.892	0.003	0.065	0.003	0.726
UNEXPMED8VAR	0.031	0.038	0.048	-0.024	0.119	-0.002	0.807
UNEXPINF	0.000	0.000	-0.001	0.046	0.730	-0.010	0.009
CPIAUCMO	0.001	0.004	0.009	0.051	0.107	-0.296	0.404
TERM	0.000	0.001	-0.001	-0.003	-0.122	1.603	-0.083
CPIMEDMO	0.030	0.039	0.048	0.001	0.036	-0.028	0.074

Table 7 shows the Pearson correlation among various factors at various sampling frequencies in the upper triangles. Covariances are shown on the diagonal and lower triangles. Variable definitions follow.

UNEXPMEDKALMAN: Unexpected Medical Inflation using the Kalman Filter methodology
UNEXPMED*x*VAR: Unxpected Medical Inflation from *x*-Variable VAR
UNEXPINF: Unexpected Aggregate Inflation
CPIAUCMO: Aggregate Inflation
TERM: Term risk premium as described in CRR (1986)
CPIMEDMO: Medical Inflation
All variables monthly

Table 8
Panel A
Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors
(January 1967-August 2009)

	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter
	P-value	P-value	P-value	P-value	P-value	P-value	P-value
Constant	1.092	0.802	0.673	0.723	0.481	0.770	0.390
	0.000	0.001	0.009	0.001	0.031	0.001	0.075
MKTRF	-0.577						
	0.097						
EXPMED		0.032				0.046	
		0.035				0.004	
ΔEXPMED			0.009				0.038
			0.648				0.028
UNEXPMED		0.099	0.087			0.048	0.047
		0.002	0.006			0.050	0.077
EXPINF				0.009		-0.010	
				0.714		0.607	
ΔEXPINF					-0.010		-0.006
					0.187		0.323
UNEXPINF				-0.007	0.025	-0.028	0.008
				0.779	0.314	0.246	0.736
N=	452	452	452	452	452	452	452

Table 8, Panel A depicts results from the second-pass of the Fama-MacBeth (1973) rolling regression procedure to assess priced risk factors in stock returns for multiple model specifications. Test assets are the 25 Fama-French quintile-sorted size and book-to-market portfolios. Shading indicates a coefficient significant at the 10% level (or p-value < 0.10). MKTRF is the market return net of the risk-free rate (taken from Ken French's Data Library). EXPMED (UNEXPMED) is the expected (unexpected) component of medical inflation as determined by a state space model described in Fama and Gibbons (1982). ΔEXPMED is the first-differenced series (i.e., time t minus time t-1) of medical inflation. Definitions for aggregate inflation (EXPINF, ΔEXPINF, and UNEXPINF) are analogous to those of medical inflation. These data series occurs between January 1967 and August 2009, for 512 months' worth of data. The second-pass results in 452 data points due to the initial 60-month beta formation period.

Table 8
Panel B
First-Pass Regression Results
(January 1967-August 2009)

	Constant	T-Stat	β_{MKTRF}	T-Stat	Adjusted R-Squared
Size (Small)					
B/M (Low)	-0.449	-2.022	1.445	30.243	0.641
B/M 2	0.254	1.318	1.230	29.681	0.633
B/M 3	0.341	2.131	1.084	31.543	0.660
B/M 4	0.556	3.590	1.005	30.208	0.641
B/M (High)	0.630	3.694	1.060	28.908	0.620
Size 2					
B/M (Low)	-0.228	-1.357	1.414	39.214	0.750
B/M 2	0.147	1.092	1.167	40.482	0.762
B/M 3	0.437	3.485	1.043	38.753	0.746
B/M 4	0.493	3.933	0.993	36.887	0.727
B/M (High)	0.506	3.262	1.086	32.570	0.675
Size 3					
B/M (Low)	-0.181	-1.300	1.348	45.075	0.799
B/M 2	0.208	2.021	1.108	50.195	0.831
B/M 3	0.298	2.841	0.985	43.660	0.789
B/M 4	0.405	3.651	0.922	38.651	0.745
B/M (High)	0.604	4.313	1.004	33.359	0.685
Size 4					
B/M (Low)	-0.029	-0.279	1.234	54.308	0.852
B/M 2	0.017	0.199	1.082	57.438	0.866
B/M 3	0.216	2.188	1.012	47.723	0.817
B/M 4	0.355	3.444	0.936	42.254	0.777
B/M (High)	0.362	2.706	1.021	35.492	0.711
Size (Big)					
B/M (Low)	-0.046	-0.597	0.991	59.417	0.874
B/M 2	0.081	1.073	0.935	57.850	0.868
B/M 3	0.031	0.340	0.871	43.827	0.790
B/M 4	0.135	1.237	0.814	34.722	0.702
B/M (High)	0.243	1.743	0.847	28.262	0.610

Table 8, Panel B shows results for the Fama-MacBeth (1973) first-pass regression for the following model.

$$R_{p,t} = \alpha_0 + \sum_{i=1}^{k} \beta_{p,i} Z_{i,t} + u_t$$

where $R_{p,t}$ is the month t excess return on portfolio *p*, *p* = 1,…,25, *t* represents time, *k* represents the number of factors, and Z_i represents a factor used to explain returns. $\beta_{p,i}$ represents a portfolio-specific parameter estimated in the model and is calculated as the covariance of the factor and portfolio return normalized by the variance of the factor (i.e., $\beta_{p,i} = cov(R_{p,i}, Z_i)/var(Z_i)$). For this specification, the portfolios p are the Fama and French size- and book-to-market sorted quintiles, *t* represents the 512 months spanning from January 1967 to August 2009, and the only factor is the market return in excess of the risk-free rate (MKTRF). Shading indicates parameters that are significant at conventional (90 percent) level.

Table 8
Panel C
First-Pass Regression Results
(January 1967-August 2009)

	Constant	T-Stat	β_{EXPMED}	T-Stat	$\beta_{UNEXPMED\ KALMAN}$	T-Stat	Adjusted R-Squared
Size (Small)							
B/M (Low)	0.767	0.617	-1.314	-0.568	-0.659	-0.295	-0.003
B/M 2	1.439	1.354	-1.420	-0.718	-1.132	-0.594	-0.002
B/M 3	1.087	1.186	-0.673	-0.394	-0.702	-0.427	-0.003
B/M 4	1.172	1.361	-0.483	-0.301	-0.571	-0.369	-0.004
B/M (High)	1.170	1.262	-0.283	-0.164	-0.032	-0.019	-0.004
Size 2							
B/M (Low)	1.218	1.081	-1.757	-0.839	-1.182	-0.585	-0.002
B/M 2	0.912	0.990	-0.620	-0.361	-1.252	-0.757	-0.003
B/M 3	1.722	2.076	-1.739	-1.127	-0.639	-0.429	-0.001
B/M 4	0.978	1.223	-0.222	-0.149	-1.341	-0.934	-0.002
B/M (High)	0.787	0.866	0.247	0.146	-0.946	-0.581	-0.003
Size 3							
B/M (Low)	1.488	1.432	-2.241	-1.159	-0.877	-0.470	-0.001
B/M 2	1.165	1.389	-1.033	-0.662	-0.842	-0.560	-0.002
B/M 3	1.226	1.604	-1.067	-0.750	-1.383	-1.008	-0.001
B/M 4	0.926	1.259	-0.322	-0.236	-1.435	-1.088	-0.002
B/M (High)	1.129	1.349	-0.268	-0.172	-0.513	-0.341	-0.004
Size 4							
B/M (Low)	1.590	1.722	-2.210	-1.287	-1.476	-0.891	0.001
B/M 2	1.206	1.501	-1.469	-0.982	-1.612	-1.118	0.000
B/M 3	0.963	1.246	-0.680	-0.472	-1.345	-0.969	-0.002
B/M 4	1.152	1.573	-0.842	-0.618	-1.348	-1.025	-0.001
B/M (High)	0.365	0.437	0.767	0.494	-1.363	-0.909	-0.002
Size (Big)							
B/M (Low)	1.600	2.187	-2.447	-1.798	-0.970	-0.739	0.003
B/M 2	1.131	1.629	-1.323	-1.024	-0.667	-0.535	-0.001
B/M 3	0.704	1.036	-0.625	-0.495	-0.370	-0.304	-0.003
B/M 4	0.233	0.347	0.442	0.354	-1.237	-1.027	-0.002
B/M (High)	1.231	1.648	-1.288	-0.927	-0.387	-0.289	-0.002

Table 8, Panel C shows results for the Fama-MacBeth (1973) first-pass regression for the following model.

$$R_{p,t} = \alpha_0 + \sum_{i=1}^{k} \beta_{p,i} Z_{i,t} + u_t$$

where $R_{p,t}$ is the month t excess return on portfolio p, p = 1,…,25, t represents time, k represents the number of factors, and Z_i represents a factor used to explain returns. $\beta_{p,i}$ represents a portfolio-specific parameter estimated in the model and is calculated as the covariance of the factor and portfolio return normalized by the variance of the factor (i.e., $\beta_{p,i} = cov(R_{p,i}, Z_i)/var(Z_i)$). For this specification, the portfolios p are the Fama and French size- and book-to-market sorted quintiles, t represents the 512 months spanning from January 1967 to August 2009, and the factors k are expected and unexpected medical inflation (EXPMED and UNEXPMEDKALMAN, respectively). Shading indicates parameters that are significant at conventional (90 percent) level.

Table 8
Panel D

	Jan 72-Aug 09	Jan 72-Dec 84	Jan 85-Aug 09
	Parameter	**Parameter**	**Parameter**
Variable	**P-Value**	**P-Value**	**P-Value**
Constant	0.770	0.377	0.977
	0.001	0.318	0.001
EXPMED	0.046	0.100	0.018
	0.004	0.008	0.206
UNEXPMED	0.048	0.207	-0.035
	0.050	0.001	0.031
EXPINF	-0.010	-0.085	0.030
	0.607	0.067	0.073
UNEXPINF	-0.028	-0.133	0.027
	0.246	0.003	0.355
N=	452	156	296

Table 8, Panel D depicts results from the second-pass of the Fama-MacBeth (1973) rolling regression procedure to assess priced risk factors in stock returns for multiple model specifications. Test assets are the 25 Fama-French quintile-sorted size and book-to-market portfolios. Coefficients significant at the 10% level (or p-value < 0.10) are shaded. EXPMED (UNEXPMED) is the expected (unexpected) component of medical inflation as determined by a state space model described in Fama and Gibbons (1982). Definitions for aggregate inflation (EXPINF and UNEXPINF) are analogous to those of medical inflation. These data series occurs between January 1967 and August 2009, for 512 months' worth of data. The second-pass results for the first specification containts 452 data points due to the initial 60-month beta formation period. The second and third specifications depict results when the sample entire sample is split into two time periods.

Table 9
Panel A
Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors-Chen, Roll, and Ross (1986) Mactoreconomic Factors
(January 1967-August 2009)

	Parameter	**Parameter**	**Parameter**	**Parameter**	**Parameter**
	P-value	**P-value**	**P-value**	**P-value**	**P-value**
Constant	0.802	0.769	1.391	0.865	1.435
	0.002	0.001	0.000	0.001	0.000
EXPMED		0.033	0.019		
		0.019	0.169		
UNEXPMED		0.054	0.052		
		0.028	0.021		
CPIMED				0.078	0.065
				0.014	0.026
MKTRF			-1.033		-1.078
			0.000		0.000
INDPRO	-0.154	-0.121	0.008	-0.102	-0.025
	0.139	0.201	0.930	0.310	0.787
ΔEXPINF	-0.003	-0.006	-0.007	-0.001	-0.004
	0.612	0.181	0.155	0.791	0.463
UNEXPINF	0.011	-0.008	-0.023	0.011	-0.013
	0.606	0.678	0.312	0.565	0.554
DEF	-0.129	-0.083	-0.075	-0.106	-0.070
	0.043	0.171	0.188	0.093	0.241
TERM	0.080	0.239	0.351	0.084	0.182
	0.585	0.090	0.007	0.549	0.147
N=	452	452	452	452	452

Table 9, Panel A depicts results from the second-pass of the Fama-MacBeth (1973) rolling regression procedure to assess priced risk factors in stock returns for multiple model specifications. Test assets are the 25 Fama-French quintile-sorted size and book-to-market portfolios. Coefficients significant at the 10% level (or p-value < 0.10) are shaded. EXPMED (UNEXPMED) is the expected (unexpected) component of medical inflation as determined by a state space model described in Fama and Gibbons (1982). MKTRF is the market return net of the risk-free rate (taken from Ken French's Data Library). INDPRO is the monthly change in Industrial Production. ΔEXPINF is the first-differenced series (i.e., time t minus time t-1) of aggregate inflation. UNEXPINF is analagous to UNEXPMEDINF but for aggregate inflation. DEF is the difference between the 10-year Treasury bond and a portfolio of Baa corporate bonds.

TERM is the difference between the 10-year Treasury bond and the 90-day Treasury bill. These data series occurs between January 1967 and August 2009, for 512 months' worth of data. The second-pass results in 452 data points due to the initial 60-month beta formation period.

Table 9

Panel B

Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors-Chen, Roll, and Ross (1986) Mactoreconomic Factors, Divided Sample (January 1967-August 2009)

	Table 9, Panel A, Column 3 (Specification 2)			**Table 9, Panel A, Column 4 (Specification 3)**		
	Jan 72-Aug 09	**Jan 72-Dec 84**	**Jan 85-Aug 09**	**Jan 72-Aug 09**	**Jan 72-Dec 84**	**Jan 85-Aug 09**
	Parameter	**Parameter**	**Parameter**	**Parameter**	**Parameter**	**Parameter**
	P-Value	**P-Value**	**P-Value**	**P-Value**	**P-Value**	**P-Value**
Constant	0.769	0.107	1.118	1.391	0.778	1.715
	0.001	0.794	0.000	0.000	0.080	0.000
EXPMED	0.033	0.059	0.019	0.019	0.033	0.011
	0.019	0.055	0.170	0.169	0.275	0.406
UNEXPMED	0.054	0.216	-0.032	0.052	0.206	-0.029
	0.028	0.001	0.045	0.021	0.000	0.072
MKTRF				-1.033	-0.672	-1.222
				0.000	0.198	0.001
INDPRO	-0.121	-0.360	0.005	0.008	0.006	0.009
	0.201	0.113	0.955	0.930	0.976	0.922
ΔEXPINF	-0.006	-0.006	-0.006	-0.007	-0.007	-0.007
	0.181	0.485	0.247	0.155	0.442	0.225
UNEXPINF	-0.008	-0.048	0.012	-0.023	-0.080	0.008
	0.678	0.190	0.606	0.312	0.057	0.771
DEF	-0.083	0.033	-0.143	-0.075	0.027	-0.128
	0.171	0.801	0.020	0.188	0.810	0.042
TERM	0.239	-0.301	0.523	0.351	-0.024	0.549
	0.090	0.194	0.003	0.007	0.906	0.001
N=	452	156	296	452	156	296

Table 9, Panel B depicts results from the second-pass of the Fama-MacBeth (1973) rolling regression procedure to assess priced risk factors in stock returns for multiple model specifications. Test assets are the 25 Fama-French quintile-sorted size and book-to-market portfolios. Coefficients significant at the 10% level (or p-value < 0.10) are shaded. EXPMED (UNEXPMED) is the expected (unexpected) component of medical inflation as determined by a state space model described in Fama and Gibbons (1982). MKTRF is the market return net of the risk-free rate (taken from Ken French's Data Library). INDPRO is the monthly change in Industrial Production. ΔEXPINF is the first-differenced series (i.e., time t minus time t-1) of aggregate inflation. UNEXPINF is analagous to UNEXPMEDINF but for aggregate inflation. DEF is the difference between the 10-year Treasury bond and a portfolio of Baa corporate bonds. TERM is the difference between the 10-year Treasury bond and the 90-day Treasury bill. These

data series occurs between January 1967 and August 2009, for 512 months' worth of data. The second-pass results in 452 data points due to the initial 60-month beta formation period. The second, third, fifth, and sixth specifications depict results when the sample entire sample is split into two time periods.

Table 10
Panel A
Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors-Flannery & Protopapadakis (2002) Mactoreconomic Factors
(January 1967- August 2009)

	Parameter	**Parameter**	**Parameter**	**Parameter**	**Parameter**
	P-Value	**P-Value**	**P-Value**	**P-Value**	**P-Value**
Constant	0.592	0.732	1.035	1.246	1.152
	0.012	0.002	0.000	0.000	0.000
EXPMED				0.036	0.039
				0.008	0.005
UNEXPMED				0.044	0.056
				0.042	0.010
CPIMED		0.083	0.077		
		0.011	0.009		
EXPINF		0.040			
		0.011			
ΔEXPINF	0.002		-0.003	-0.001	0.003
	0.765		0.614	0.793	0.624
UNEXPINF	0.014	-0.003	0.007	-0.007	-0.009
	0.541	0.908	0.764	0.769	0.708
PPIAgg	0.123	0.105	0.118	0.062	0.052
	0.118	0.243	0.166	0.473	0.575
PPICrude	-0.089	0.015			0.414
	0.794	0.969			0.271
M1	-0.081	-0.149	-0.076	-0.035	-0.022
	0.162	0.016	0.187	0.535	0.703
M2	-0.127	-0.156	-0.095	-0.088	-0.079
	0.002	0.000	0.010	0.010	0.024
HOUST	-2.234	-1.906	-1.721	-1.977	-1.238
	0.014	0.034	0.060	0.031	0.166
MKTRF			-0.716	-0.906	-0.797
			0.011	0.002	0.008
N=	452	452	452	452	452

Table 10, Panel A depicts results from the second-pass of the Fama-MacBeth (1973) rolling regression procedure to assess priced risk factors in stock returns for multiple model specifications. Test assets are the 25 Fama-French quintile-sorted size and book-to-market portfolios. Coefficients significant at the 10% level (or p-value < 0.10) are shaded. EXPMED

(UNEXPMED) is the expected (unexpected) component of medical inflation as determined by a state space model described in Fama and Gibbons (1982). CPIMED is aggregate medical inflation, or the sum of expected and unexpected medical inflation. ΔEXPINF is the first-differenced series (i.e., time t minus time t-1) of aggregate inflation. UNEXPINF is analagous to UNEXPMEDINF for aggregate inflation. PPIAgg (PPICrude) is the monthly change in Producer Price Index for all commodities (crude materials). M1 (M2) is the monthly change in M1 (M2) Money Stock, seasonally adjusted. HOUST is the monthly change in total new housing starts. The prior 5 series come from the St. Louis Federal Reserve Federal Reserve Economic Database (FRED). MKTRF is the market return net of the risk-free rate from Ken French's Data Library. These data series occurs between January 1967 and August 2009, for 512 months' worth of data. The second-pass results in 452 data points due to the initial 60-month beta formation period.

Table 10
Panel B
Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors-Flannery & Protopapadakis (2002) Macroeconomic Factors, Divided Sample
(January 1967- August 2009)

	Table 10, Panel A, Specification 4		
	Jan 72-Aug 09	Jan 72-Dec 84	Jan 85-Aug 09
	Parameter	Parameter	Parameter
	P-Value	P-Value	P-Value
Constant	1.246	0.914	1.420
	0.000	0.054	0.000
EXPMED	0.036	0.080	0.013
	0.008	0.012	0.287
UNEXPMED	0.044	0.184	-0.030
	0.042	0.001	0.035
CPIMED			
EXPINF			
ΔEXPINF	-0.001	-0.003	0.000
	0.793	0.741	0.966
UNEXPINF	-0.007	-0.069	0.026
	0.769	0.090	0.358
PPI (Agg)	0.062	-0.178	0.189
	0.473	0.308	0.048
PPI (Crude)			
M1	-0.035	0.007	-0.057
	0.535	0.927	0.456
M2	-0.088	-0.112	-0.075
	0.010	0.081	0.060
HOUST	-1.977	-0.805	-2.594
	0.031	0.625	0.018
MKTRF	-0.906	-0.794	-0.966
	0.002	0.136	0.005
N=	452	156	296

Table 10, Panel B depicts results from the second-pass of the Fama-MacBeth (1973) rolling regression procedure to assess priced risk factors in stock returns for multiple model specifications. Test assets are the 25 Fama-French quintile-sorted size and book-to-market portfolios. Coefficients significant at the 10% level (or p-value < 0.10) are shaded. EXPMED (UNEXPMED) is the expected (unexpected) component of medical inflation as determined by a state space model described in Fama and Gibbons (1982). CPIMED is aggregate medical inflation, or the sum of expected and unexpected medical inflation. ΔEXPINF is the first-differenced series (i.e., time t minus time t-1) of aggregate inflation. UNEXPINF is analagous to UNEXPMEDINF for aggregate inflation. PPIAgg (PPICrude) is the monthly change in Producer Price Index for all commodities (crude materials). M1 (M2) is the monthly change in M1 (M2) Money Stock, seasonally adjusted. HOUST is the monthly change in total new housing starts. The prior 5 series come from the St. Louis Federal Reserve Federal Reserve Economic Database (FRED). MKTRF is the market return net of the risk-free rate from Ken French's Data Library. These data series occur between January 1967 and August 2009, for 512 months' worth of data. The second-pass results in 452 data points due to the initial 60-month beta formation period. The second and third specifications depict results when the sample entire sample is split into two time periods.

Table 11
Panel A
Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors-Statistical Factors
(January 1967-August 2009)

	Parameter	**Parameter**	**Parameter**	**Parameter**	**Parameter**	**Parameter**	**Parameter**	**Parameter**	**Parameter**
	P-Value	**P-Value**	**P-Value**	**P-Value**	**P-Value**	**P-Value**	**P-Value**	**P-Value**	**P-Value**
Constant	1.154	1.159	1.096	1.310	1.218	1.234	1.317	1.261	1.266
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
EXPMED		0.027			0.032			0.039	
		0.022			0.006			0.002	
UNEXPMED		0.004			0.001			0.002	
		0.827			0.952			0.918	
CPIMED			0.001			0.001			0.004
			0.975			0.954			0.866
MKTRF	-0.852	-0.815	-0.784	-1.018	-0.893	-0.925	-1.007	-0.930	-0.949
	0.001	0.002	0.002	0.000	0.001	0.001	0.000	0.001	0.001
SMB	0.072	0.083	0.079	0.080	0.091	0.077	0.082	0.097	0.079
	0.633	0.578	0.601	0.599	0.545	0.606	0.585	0.511	0.595
HML	0.523	0.499	0.521	0.512	0.506	0.510	0.514	0.488	0.508
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
DEF				-0.038	-0.061	-0.045	-0.065	-0.078	-0.111
				0.492	0.246	0.424	0.241	0.151	-0.064
TERM				0.210	0.299	0.253	0.191	0.292	0.236
				0.074	0.013	0.036	0.119	0.021	0.062
MOM							-0.259	-0.395	-0.258

							0.358	0.193	0.371
N=	452	452	452	452	452	452	452	452	452

Table 11, Panel A depicts results from the second-pass of the Fama-MacBeth (1973) rolling regression procedure to assess priced risk factors in stock returns for multiple model specifications. Test assets are the 25 Fama-French quintile-sorted size and book-to-market portfolios. Coefficients significant at the 10% level (or p-value < 0.10) are shaded. EXPMED (UNEXPMED) is the expected (unexpected) component of medical inflation as determined by a state space model described in Fama and Gibbons (1982). CPIMED is aggregate medical inflation, or the sum of expected and unexpected medical inflation. MKTRF is the market return net of the risk-free rate. SMB is calculated by subtracting the return of the decile of the largest stocks—by market capitalization—from the decile of smallest stocks. HML is calculated by subtracting the return of the stock decile having the lowest book-to-market equity ration from the decile with the highest book-to-market ratio. See Fama and French (1993) for additional details regarding MKTRF, SMB, and HML. DEF is the difference between the 10-year Treasury bond and a portfolio of Baa corporate bonds. TERM is the difference between the 10-year Treasury bond and the 90-day Treasury bill. MOM is a momentum factor found by subtracting the returns of a stock portfolio having the lowest recent returns from a portfolio having the highest recent returns. MKTRF, SMB, HML, and MOM come from Ken French's Data Library. These data series occurs between January 1967 and August 2009, for 512 months' worth of data. The second-pass results in 452 data points due to the initial 60-month beta formation period.

Table 11
Panel B
Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors-Statistical Factors, Divided Sample
(January 1967-August 2009)

	Table 11, Panel A, Specification 8		
	Jan 72-Aug 09	**Jan 72-Dec 84**	**Jan 85-Aug 09**
	Parameter	**Parameter**	**Parameter**
	P-Value	**P-Value**	**P-Value**
Constant	1.261	0.627	1.595
	0.000	0.230	0.000
EXPMED	0.039	0.078	0.018
	0.002	0.003	0.152
UNEXPMED	0.002	0.079	-0.039
	0.918	0.105	0.008
MKTRF	-0.930	-0.538	-1.136
	0.001	0.325	0.001
SMB	0.097	0.258	0.013
	0.511	0.277	0.946
HML	0.488	0.798	0.324
	0.001	0.001	0.085
DEF	-0.078	0.056	-0.149
	0.151	0.566	0.021
TERM	0.292	-0.076	0.486
	0.021	0.720	0.002
MOM	-0.395	-0.263	-0.464
	0.193	0.498	0.264
N=	452	156	296

Table 11, Panel B depicts results from the second-pass of the Fama-MacBeth (1973) rolling regression procedure to assess priced risk factors in stock returns for multiple model specifications. Test assets are the 25 Fama-French quintile-sorted size and book-to-market portfolios. Coefficients significant at the 10% level (or p-value < 0.10) are shaded. EXPMED (UNEXPMED) is the expected (unexpected) component of medical inflation as determined by a state space model described in Fama and Gibbons (1982). MKTRF is the market return net of the risk-free rate. SMB is calculated by subtracting the return of the decile of the largest stocks—by market capitalization—from the decile of smallest stocks. HML is calculated by subtracting the return of the stock decile having the lowest book-to-market equity ration from the decile with the highest book-to-market ratio. See Fama and French (1993) for additional details regarding

MKTRF, SMB, and HML. DEF is the difference between the 10-year Treasury bond and a portfolio of Baa corporate bonds. TERM is the difference between the 10-year Treasury bond and the 90-day Treasury bill. MOM is a momentum factor found by subtracting the returns of a stock portfolio having the lowest recent returns from a portfolio having the highest recent returns. MKTRF, SMB, HML, and MOM come from Ken French's Data Library. These data series occurs between January 1967 and August 2009, for 512 months' worth of data. The second-pass results in 452 data points due to the initial 60-month beta formation period. The second and third specifications depict results when the sample entire sample is split into two time periods.

Table 12
Panel A
Fama-MacBeth (1973) First-Pass Time Series Results for Priced Factors
(January 1967-December 2008)

	β_{MedHML}	T-Stat	β_{MKTRF}	T-Stat	β_{SMB}	T-Stat	β_{HML}	T-Stat	β_{DEF}	T-Stat	β_{TERM}	T-Stat	β_{MOM}	T-Stat	Adj R-sq
Size (Small)															
B/M (Low)	16.49	4.07	1.13	43.06	1.31	37.38	-0.30	-7.60	-0.38	-2.22	-0.10	-1.15	-0.03	-0.99	0.93
B/M 2	5.22	1.78	0.99	52.17	1.27	50.39	0.06	2.12	-0.15	-1.21	-0.02	-0.28	0.01	0.29	0.95
B/M 3	1.49	0.62	0.94	60.42	1.05	50.68	0.30	12.85	0.17	1.68	0.00	-0.03	0.03	1.73	0.95
B/M 4	4.52	1.79	0.90	54.72	0.97	44.66	0.44	17.81	0.24	2.25	0.01	0.18	0.02	1.24	0.94
B/M (High)	5.95	2.26	1.01	58.74	1.05	45.86	0.67	25.69	-0.22	-2.00	0.12	2.14	-0.03	-1.78	0.94
Size 2															
B/M (Low)	-2.40	-0.81	1.16	60.40	1.00	39.02	-0.37	-12.56	-0.12	-0.93	-0.05	-0.75	-0.04	-2.07	0.95
B/M 2	-10.25	-3.76	1.06	59.79	0.87	36.84	0.18	6.74	0.15	1.36	-0.10	-1.80	-0.02	-1.23	0.94
B/M 3	-5.02	-1.98	1.00	60.76	0.75	34.03	0.44	17.37	0.20	1.92	0.04	0.77	0.00	-0.18	0.93
B/M 4	-7.68	-3.06	0.99	60.83	0.71	32.97	0.58	23.22	0.05	0.45	0.00	0.00	-0.01	-0.42	0.93
B/M (High)	-7.21	-2.75	1.10	64.72	0.87	38.61	0.79	30.35	-0.06	-0.58	0.03	0.49	-0.01	-0.48	0.94
Size 3															
B/M (Low)	-2.40	-0.84	1.11	59.76	0.74	30.15	-0.44	-15.66	-0.20	-1.69	0.03	0.46	-0.05	-2.53	0.95
B/M 2	-4.41	-1.42	1.09	53.91	0.51	19.10	0.25	8.10	0.26	1.98	0.00	-0.05	-0.02	-1.00	0.91
B/M 3	-7.84	-2.66	1.03	53.45	0.42	16.43	0.50	17.24	0.29	2.32	-0.05	-0.78	-0.02	-0.86	0.89
B/M 4	-5.73	-2.00	1.02	54.63	0.36	14.68	0.65	23.13	0.22	1.82	0.00	-0.03	-0.01	-0.72	0.89
B/M (High)	-3.02	-0.88	1.09	49.21	0.51	17.16	0.80	23.67	0.45	3.17	-0.06	-0.89	-0.05	-2.30	0.88
Size 4															
B/M (Low)	-0.48	-0.18	1.09	63.73	0.40	17.67	-0.40	-15.51	0.00	0.01	-0.03	-0.58	-0.01	-0.48	0.95

B/M 2	-8.00	-2.48	1.13	54.02	0.23	8.40	0.28	8.67	0.32	2.34	-0.09	-1.29	-0.03	-1.32	0.89
B/M 3	-6.12	-1.86	1.13	52.76	0.17	6.12	0.52	15.88	0.15	1.09	-0.07	-1.08	-0.05	-2.23	0.88
B/M 4	-8.80	-3.03	1.05	55.62	0.20	8.00	0.62	21.41	0.15	1.21	-0.12	-2.03	-0.02	-1.23	0.89
B/M (High)	-0.79	-0.22	1.15	50.13	0.19	6.15	0.79	22.63	-0.05	-0.33	-0.02	-0.21	-0.04	-1.71	0.87
Size (Big)															
B/M (Low)	-2.99	-1.34	0.97	66.51	-0.27	-13.89	-0.37	-16.87	-0.09	-0.96	0.06	1.39	-0.02	-1.29	0.94
B/M 2	-7.45	-2.67	1.03	56.76	-0.21	-8.68	0.13	4.62	0.20	1.71	-0.01	-0.21	0.01	0.29	0.89
B/M 3	-4.09	-1.31	1.01	49.38	-0.23	-8.40	0.31	9.90	0.01	0.05	0.00	0.03	0.02	1.11	0.85
B/M 4	-1.25	-0.48	1.00	58.18	-0.21	-9.26	0.62	23.65	0.02	0.19	-0.12	-2.14	-0.06	-3.53	0.89
B/M (High)	4.39	1.08	1.05	39.38	-0.11	-3.22	0.77	18.96	-0.07	-0.39	-0.03	-0.30	-0.04	-1.53	0.79

Table 12, Panel A shows results for the Fama-MacBeth (1973) first-pass regression for the following model.

$$R_{p,t} = \alpha_0 + \sum_{i=1}^{k} \beta_{p,i} Z_{i,t} + u_t$$

where $R_{p,t}$ is the month t excess return on portfolio p, p = 1,…,25, t represents time, k represents the number of factors, and Z_i represents a factor used to explain returns. $\beta_{p,i}$ represents a portfolio-specific parameter estimated in the model and is calculated as the covariance of the factor and portfolio return normalized by the variance of the factor (i.e., $\beta_{p,i} = cov(R_{p,i}, Z_i)/var(Z_i)$). For this specification, the portfolios p are the Fama and French size- and book-to-market sorted quintiles, t represents the 504 months spanning from January 1967 to December 2008, and the factors k are described as follows. MedHML is the return formed by subtracting the returns of a portfolio having a low beta with medical inflation from the returns of a portfolio having a high beta with medical inflation. These portfolios are formed by sorting individual stocks into quintiles based on their medical inflation beta. MKTRF is the market return net of the risk-free rate. SMB is calculated by subtracting the return of the decile of the largest stocks—by market capitalization—from the decile of smallest stocks. HML is calculated by subtracting the return of the stock decile having the lowest book-to-market equity ration from the decile with the highest book-to-market ratio. See Fama and French (1993) for additional details regarding MKTRF, SMB, and HML. DEF is the difference between the 10-year Treasury bond and a portfolio of Baa corporate bonds. TERM is the difference between the 10-year Treasury bond and the 90-day Treasury bill. MOM is a momentum factor found by subtracting the returns of a stock portfolio having the lowest recent returns from a portfolio having the highest recent returns. Shading indicates parameters that are significant at conventional (90 percent) level.

Table 12
Panel B
Fama-MacBeth (1973) Second-Pass Cross-Sectional Results for Priced Factors, with Divided Sample
(January 1967-December 2008)

	Jan 77-Dec 08	Jan 77-Dec 84	Jan 85-Dec 08
	Parameter	Parameter	Parameter
	P-value	P-value	P-value
CONSTANT	1.442	0.124	1.882
	0.000	0.801	0.000
MedHML	-0.006	-0.006	-0.006
	0.039	0.180	0.096
MKTRF	-1.021	-0.225	-1.286
	0.002	0.757	0.000
SMB	0.082	0.270	0.019
	0.642	0.449	0.926
HML	0.539	0.709	0.483
	0.001	0.015	0.015
DEF	0.108	0.121	0.103
	0.101	0.461	0.133
TERM	0.103	0.047	0.122
	0.466	0.865	0.460
MOM	1.393	0.569	1.667
	0.000	0.295	0.000
N=	384	96	288

Table 9, Panel B depicts results from the second-pass of the Fama-MacBeth (1973) rolling regression procedure to assess priced risk factors in stock returns for multiple model specifications. Test assets are the 25 Fama-French quintile-sorted size and book-to-market portfolios. Coefficients significant at the 10% level (or p-value < 0.10) are shaded. MedHML is the return formed by subtracting the returns of a portfolio having a low beta with medical inflation from the returns of a portfolio having a high beta with medical inflation. These portfolios are formed by sorting individual stocks into quintiles based on their medical inflation beta. MKTRF is the market return net of the risk-free rate. SMB is calculated by subtracting the return of the decile of the largest stocks—by market capitalization—from the decile of smallest stocks. HML is calculated by subtracting the return of the stock decile having the lowest book-to-market equity ration from the decile with the highest book-to-market ratio. See Fama and French (1993) for additional details regarding MKTRF, SMB, and HML. DEF is the difference between the 10-year Treasury bond and a portfolio of Baa corporate bonds. TERM is the difference between the 10-year Treasury bond and the 90-day Treasury bill. MOM is a

momentum factor found by subtracting the returns of a stock portfolio having the lowest recent returns from a portfolio having the highest recent returns. MKTRF, SMB, HML, and MOM come from Ken French's Data Library. These data series occur between January 1967 and December 2008, for 504 months' worth of data. 60 months' of data are used to generate the medical inflation surprise beta coefficient to create deciles, leaving 444 months for the two-pass method. The second-pass in this case results in 384 data points due to the initial 60-month beta formation period. The second and third specifications depict results when the entire sample is split into two time periods.

Appendix C:
Using State Space Models to Disentangle Expected and Unexpected Inflation

The Kalman filter model is a state-space representation where model parameters are continually updated to reflect new information. The model establishes dynamic parameter values and facilitates finite-sample forecasts. This Appendix presents a brief summary of the topic, which follows Hamilton (1994a), to which the reader is referred for a more extensive treatment.

The generic state-space representation of the dynamics of an observed variable y associated with an unobserved variable ψ is given by the following system.

$$\psi_{t+1} = F\psi_t + v_{t+1} \quad (1)$$

$$y_t = A'x_t + H'\psi_t + w_t \quad (2)$$

where F, A', and H' are matrices and x_t is a vector of exogenous variables, which could include lagged values of y if uncorrelated with ψ and w at all leads and lags. Equation (1) represents the state or transition equation; equation (2) the observation or measurement equation. The two error series v and w are shocks to the respective transition process and measurement equation, respectively, and represent white noise. Assumptions in this model are that the error terms are uncorrelated at all lags, x is uncorrelated with all lags of ψ and w, and the system's observations are a finite series with the first unobservable state ψ uncorrelated with all subsequent shock (i.e., v and w) values.

Given this general setup, Fama and Gibbons (1982) investigate the unobservable ex ante real interest rate, ψ, which is a function of the nominal interest rate (i.e., lagged Treasury bill), i, inflation, I, and the average ex ante real interest rate, r, according to Fisher (1930) and represented by equation (3).

$$\psi_t = i_t - E(I)_t - r \quad (3)$$

where E(*) is the expectations operator. Assuming the expected real interest rate follows an AR(1) process, the state equation becomes (4) below.

$$\psi_{t+1} = \rho\psi_t + v_{t+1} \quad (4)$$

Since we have observations on the ex post real interest rate, which is the nominal interest rate minus actual inflation, we can write the measurement equation as follows.

$$i_t - I_t = (i_t - E(I)_t) + (E(I)_t - I_t) \quad (5)$$

or substituting from (3),

$$i_t - I_t = r + \psi_t + (E(I)_t - I_t) = r + \psi_t + u_t \quad (6)$$

where u_t equals $(E(I)_t - I_t)$, or the negative value of unexpected inflation. This term represents error in the inflation forecast. If these inflation forecasts are made in optimal fashion, then these errors, u_t, should be uncorrelated with their lags and with the ex ante real interest rate, ψ_t. Thus the conditions of equation (2) are met, and one can see how the general Kalman filter model in

equations (1) and (2) apply when we let F = ρ, $y_t = i_t - I_t$, $A'x = r$, and $H' = 1$ to get the following system.

$$\psi_{t+1} = \rho\psi_t + v_{t+1}$$

$$i_t - I_t = r + \psi_t + u_t = r + \psi_t + (E(I)_t - I_t)$$

Using the Dynamic Linear Model (DLM) capability in the RATS computer program and setting initial values of 0.1 for the coefficient on the nominal interest rate (i.e., lagged Treasury bill), i, and 1.0 for the variances of the error terms v and u, we iteratively solve this system to extract the time-varying constant parameter. Doing so in turn allows us to separate aggregate inflation into its unexpected and expected components.

Essay #2: Using Genetic Algorithms for Hedging Health Care Costs, Managing Macroeconomic Risk, and Tracking Investments

Introduction

The intuition behind a natural hedge is straightforward enough, and can be easily illustrated through example. If an individual is concerned about wealth decreases from rising gasoline and heating oil prices, then he or she could offset the wealth decreases by investing in oil companies (with fixed production factor costs). Likewise, one would think it is possible to offset health care costs by investing in health care-related firms. Empirically, however, this natural hedge for health care does not exist according to the analysis in Jennings, Fraser, and Payne (2009). By investigating the correlation between various investable health care mutual funds and health care inflation, they find these funds do a poor job of hedging health care costs that have outpaced general inflation since the mid-1980s. Since hedging such non-investable macroeconomic factors has substantial practical relevance for health care and beyond, the purpose of this paper is to present an implementable technique to form a hedging or risk management strategy. Narrowly, this research demonstrates the ability of a genetic algorithm (GA) methodology to identify a portfolio of assets that offsets the risk posed by monthly medical inflation. More broadly, the GA procedure implemented here could be used to find risk-managing portfolios for virtually any non-investable time series, representing a significant risk management tool. Further, the technique translates directly into creating portfolios that mimic investable assets. This paper illustrates the tool's flexibility by demonstrating its ability to find asset portfolios that track mutual funds and exchange-traded funds (ETFs).

Literature Review

We provide a brief summary of GAs here, referring the interested reader to Bauer (1994) for a more detailed description and Holland (1975) for the mathematical proofs behind the methods. A genetic algorithm (GA) is an iterative computational method based on an analogy with Darwinian natural selection and mutation. As with any optimization method, a GA begins with choosing an objective function. In this application, the first objective is to minimize the variance of a hedged portfolio consisting of a "short" position in medical inflation and a long position in a portfolio of investable assets. Following the analogy of natural selection, a particular candidate solution is known as an "individual" while the extent to which a particular candidate solution meets this objective is known as the "fitness" of the individual. The mechanical details of this paper's GA application are given in the Methods section. Holland (1975) provides the eloquent math demonstrating the efficiency of this problem-solving methodology.

The contribution of this effort consists of using the GA method to create parsimonious economic tracking or risk management portfolios. The Bauer (1994) presentation focuses on using GAs to generate trading strategies based on certain rules, but to our knowledge nowhere has anyone (publicly) discussed implementing them to generate portfolios that offset the risk posed by uninvestable macroeconomic series. On the other hand, Lamont (2001) describes a model that uses 13 stock and bond portfolios—while controlling for other lagged variables—to predict future macroeconomic time series. His method is exclusively regression-based and assumes investment in all 13 stock and bond portfolios, or essentially the market, to track each of the 7 macroeconomic series he investigates. While (aggregate) inflation is among the

macroeconomic series he looks at, he does not assess these 13 assets' ability to predict the medical component of inflation. While medical inflation (CPIMEDSL) has outpaced aggregate inflation (CPIAUCSL) since the early-1980s (see Figure 1), we nonetheless suspect his main conclusions would hold for medical inflation, too. For future reference, Appendix A includes all figures, and Appendix B includes all tables. Our contribution beyond Lamont's (2001) efforts is to use a completely different tool to find more parsimonious, flexible, and perhaps better-performing, set of investable assets to track a non-investable (e.g., macroeconomic) series.

GAs lend themselves to the medical cost hedging problem presented in Jennings, Fraser, and Payne (2009) for a variety of reasons, especially when compared to using a straightforward multiple regression approach. First, multiple regressions typically satisfy a single objective function: minimize the mean-squared error between the estimated and actual data. While this might be the appropriate objective function for a GA to solve, it is flexible enough to solve other objective functions as well. For instance, perhaps one desires a portfolio prohibiting short-selling. One can implement a rule for positive asset weights and then implement a GA to solve this problem. Additionally, since the GA is not a hill-climbing algorithm, it is capable of handling non-linear as well as discontinuous objective functions. In all, as evidenced with the example in this paper, the iterative nature of the GA allows for much more flexibility and control over the desired objective function than a multiple regression.

Besides their adaptability, GAs are computationally efficient. For the purpose of this research, there exist literally tens of thousands of possible investable assets worldwide that one could use to find the best hedge against medical inflation in this

country. Unfortunately the lack of data and degrees of freedom make it impossible to run a multiple regression using all these assets in a single model. In this instance, since the sample includes monthly medical inflation values between January 1967 and August 2009, there are only 512 data points. Using too many assets as independent variables quickly consumes degrees of freedom. Further, if one were to explore combinations of sub-samples of the assets, an exhaustive search of the combinations could take months or years to complete.[13] Obviously the hedging strategy in such a case could become obsolete by the time it is discovered. Besides computational considerations, another advantage of GAs relates to parsimony and user-defined objectives. For example, transactions costs play a role in any applied investment decisions. By stipulating the number and population of traded assets, users have greater control over these transactions costs. Alternatively, using an exhaustive multiple regression solution could encourage the investor to trade every asset in the model depending on the weights assigned to each asset.

As Bauer (1994) highlights, there certainly exists a major caveat to GAs. Because of their iterative nature and the sensitivity to the user-defined inputs (e.g., initial population, breeding population, amount of gene crossover, mutation frequency and method, etc.), there exists a real probability that a GA will not find the single optimal solution. However, as he demonstrates, it will generally find near-optimal solutions, and in some cases *the* optimal solution. It is possible the GA will converge too quickly on a sub-optimal solution. As he further articulates, however, in a practical sense achieving

[13] As a simple example, if one wanted to select 5 assets from a population of 300 assets, there exist over 19.6 billion unique combinations. If a computer processes 1000 multiple regressions per second, then an exhaustive analysis would take over 7.5 months to complete. The processing time further increases with portfolio size and the asset population.

the time-consuming optimal solution can become less-preferred than the quickly-developed acceptable one. Thankfully certain researchers, such as De Jong (1975) have quite effectively established appropriate input values and quantified the sensitivity to changes in them. Given the unique problem in this paper, the GA methodology generally adheres to convention and uses these recommended input values, but we also provide rationale for any deviations.

Data

Before describing the GA methodology employed, it is useful to outline data sources briefly. Medical inflation comes courtesy of the Federal Reserve Economic Database (FRED) hosted online by the Federal Reserve Bank in St. Louis. The security returns as well as the long and short government bonds and Treasury bill rates come from the Center for Research in Security Prices (CRSP).

Genetic Algorithm Methodology and Proof of Concept

Before applying the GA to actual medical inflation values, we test the GA method using a set of representative artificial assets to ensure that it works as intended. Since a perfect hedging instrument would track a target series perfectly, the objective in this "proof of concept" is to minimize the variance of the return difference between an equally-weighted portfolio of five hedging assets and the target according to equation (1) below. Clearly zero variance would mean the hedging portfolio tracks the target precisely. But from a risk management standpoint, it could also prove desirable if the hedged portfolio systematically earns higher returns than the target series even if it does

not track the target precisely (i.e., $Error_t > 0$ for most or all periods *t*). We discuss this auxiliary goal later when using the GA in a real-world application.

$$Minimize\ Variance(Error) \quad (1)$$

$$\text{where } Error_t = Ret_{Hedge\ Portfolio\ ,t} - Ret_{Target\ ,t}$$

$Ret_{Target\ ,t}$ ($Ret_{Hedge\ Portfolio\ ,t}$) is the return of the target (hedge portfolio) at time t.

In this "proof of concept" optimization, the choice variables that accomplish the objective are a set of five assets chosen from a universe of 3,000 assets. These 3,000 assets are a random subsample of over 16,000 stocks from CRSP that have at least 60 months of returns between 1967 and 2009. In the vernacular of a GA, the universe of assets is known as the "population," and the choice variables are known as "genes." A set of genes then composes the "individual." In this case there exist five assets (genes) that compose each portfolio (individual). The goal of the GA is then to form a hedge portfolio by choosing a subset of five assets (i.e., genes) out of the universe of 3,000 assets (i.e., population) that has the minimum error variance over the investment horizon. In GA terms, the goal is to find an "individual" that has a set of "genes" that generates the highest "fitness" among the "population of individuals."

To illustrate the method, we must first define and quantify how well a potential solution meets the objective function. Doing so means choosing 5 assets: i, j, k ,l and m, from 3,000 assets without replacement and equally weighting their returns to form a hedge asset with a return series given by equation (2).

$$Ret_{Hedge\ ,t} = 0.2 * Ret(i)_t + 0.2 * Ret(j)_t + 0.2 * Ret(k)_t + 0.2 * Ret(l)_t + 0.2 * Ret(m)_t \quad (2)$$

In this equation, $Ret(x)_t$ represents the return on a particular asset at time t, and the 0.2 coefficients represent the equal-weighting of each asset.

Next we construct a target portfolio according to equation (3),

$$Ret_{Target,t} = a_1 * MKTRF_t + a_2 * SMB_t + a_3 * HML_t + a_4 * DEF_t + a_5 * TERM_t \quad (3)$$

where $MKTRF_t$ is the monthly value-weighted market return in excess of the risk-free rate, SMB_t is Small-minus-Big, calculated by subtracting the return of the decile of the largest stocks—by market capitalization—from the decile of smallest stocks, and HML_t is High-minus-Low, calculated by subtracting the return of the stock decile having the lowest book-to-market equity ratio from the decile with the highest book-to-market equity ratio. These values come straight from Ken French's data library.[14] We calculate DEF_t, the default risk premium, by subtracting the long government bond yield from a Baa-and-below portfolio yield of similar duration corporate bonds and $TERM_t$, the term risk premium, by subtracting the one-month Treasury yield from the long government bond yield. Importantly, a_i is the median value of the distribution of coefficients resulting from 3,000 separate time series regressions of each of our 3,000 assets on these five factors, MKTRF, SMB, HML, DEF, and TERM. Creating a target return series in this manner ensures the target is at least reasonably representative of a return series that is part of the population of assets. That is, using the "median" asset as the target ensures the target is not an outlier we are trying to mimic, or track. While we subsequently use a "real" time series as the target, for this proof of concept we simply wish to ensure the GA tool finds a good solution for a representative target series. To make sure the solution has a reasonable chance at tracking the target series, we deliberately place the target near the

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

heart of the joint distribution of all the tracking assets. If the GA technique works as anticipated, we should expect five assets to track the target quite well in this proof of concept.

Having a target series along with a sample of possible assets to include in a hedging portfolio, we then create 1,000 “parent” portfolios, or candidate solutions, which are random combinations of five assets. This set is defined as the initial population (see Figure 2). Each candidate in turn has a quantifiable fitness level according to the objective function described in equation (1). Establishing the initial parent portfolios and their respective fitness levels initializes the GA algorithm and leads to subsequent iterations, whose goal is to improve the best solution.

The GA improves on the population of initial candidate solutions by creating new candidates as partial combinations of existing population members. The production of new candidate solutions is known in the GA literature as a “breeding.” The process begins by first ordering the initial population according to its fitness level as shown in Figure 3, Panel A. The population is then divided into two groups, called the “breeding” population and “non-breeding population.” For this study, we retain the best-fit 10-percent members as the breeding population and the remaining 90-percent as non-breeding members. New candidate solutions come only from the breeding population, and a new candidate is formed by randomly pairing two members of this breeding population. For example, using the results in Figure 3, Panel A, the first new candidates could be formed from candidates1000 and 2. The next pair considered might be 1 and 721. Keeping with the natural selection analogy, the pre-existing or current two candidate solutions are called “parents.” The parents are each defined by their gene

sequence (candidate 1000 by assets 2, 6, 28, 7 and 11 and candidate 2 by assets 23, 9, 7, 29 and 31). A breeding produces two new candidate solutions, or offspring, as follows. We randomly generate an integer between 1 and 3. This integer, called the crossover number, indicates how many genes (counted from the left) from the two parents to swap in generating two new candidate solutions called "offspring." For example, for the first pairing, if the crossover number is 2, then the two new offspring would be as shown in Figure 3, Panel B. In the second pairing (see Panel C), if the crossover number is 3, Offspring 3 and 4 would be as shown. This process continues until enough pairings have occurred for the breeding population to replace the non-breeding group. Using our parameters, since we have 1,000 members in the population, 100 serve as the breeding population, leaving 900 to be replaced through the breeding process. Thus we perform 450 pairings to generate the 900 replacement members.

The next step is to evaluate the fitness level of each offspring using the process described for the initial population (see equation (1)). Finally, we modify the existing population by determining whether the offspring have better fitness levels than their parents. If a particular offspring has a fitness measure better than one of its parents, then we replace one member of the non-breeding population with the superior offspring. Doing so guarantees that the offspring has higher fitness than the candidate solution it replaces because of the original sorting of the population by fitness and division into breeding and non-breeding groups. If an offspring has an inferior fitness level compared to its parents, then the offspring does not go into the population but instead becomes replaced with a new candidate whose assets are chosen at random. This scenario represents random mutation in the population's gene pool. As with the other members,

we calculate the fitness level of this new candidate and replace one member of the non-breeding population with this new candidate. Doing so at worst weakens the non-breeding population but at best creates a mutation that will move into the breeding population for the next generation. After repeating this process for all the offspring, we again sort the population of candidate solutions by fitness level. This entire series of calculations is known as creating a "generation." The breeding population (top 10-percent most fit) after each generation will weakly dominate both the initial and prior population.

The GA approach quickly converges to (near) optimal solutions by two mechanisms. First, the algorithm exploits the fact that a group of "good" solutions will generally contain similar features; in our case this group of assets forms a good hedging portfolio for a target series. By selectively swapping combinations of assets among candidates that are by themselves good solutions, better candidates emerge. The second feature a GA exploits is a concept called "implicit parallel processing." In our application, we have 5 assets to choose out of a population of 3,000 assets, or $\binom{3{,}000}{5}$ possible hedges. If, after several generations, the algorithm determines that asset 20 does not contribute to overall fitness, then the algorithm has effectively eliminated *all* candidates that include asset 20. Doing so means that $\binom{2{,}999}{4}$ candidates have implicitly been eliminated from consideration.[15] The combination of these two features allows the GA to cover a vast number of candidate solutions very rapidly.

Running the proof of concept for multiple generations provides encouraging results. Table 1 shows the generation-by-generation results of the GA for 10 generations.

[15] There would be 2,999 other assets to choose from once asset 20 was eliminated and 4 assets to choose.

The generation-by-generation population minimum, mean, and maximum fitness levels vary quite substantially. Again, we calculate these fitness levels using Equation (1), and our goal is to minimize the fitness value. The final column shows the mean fitness level for only the breeding population by generation, or the top 100-performing portfolios in this construction. As expected, the minimum fitness values decrease (Column 2), or improve, over generations until a certain point at which convergence likely occurs. In this instance the minimum value appears to converge in the fifth generation. Notably, the mean and maximum (i.e., worst) fit of the population fluctuate over time, which occurs because we allow substantial mutation from generation to generation. We notice two things about the mean fit of the breeding population (Column 5). First, its fitness value steadily improves (i.e., decreases) asymptotically over time. Secondly, the breeding population has converged to the minimum value shown in Column 2 by the eighth generation. Thus the "best" solution has bred out all other possibilities, and the only possible further improvement would come from mutations in future generations.

Figure 4, Panel A shows a graphical representation of the monthly returns for the hedge portfolio for the best solution (RETURNHEDGE), which is an equally-weighted portfolio of assets indexed by numbers 2745, 2432, 2011, 1086, and 2151 (of our 3,000 original assets), and the target return series (TARGET) between January 1967 and August 2009. Again, equation (2) shows how we calculate the notional target series. The correlation between these two series exceeds 0.96. Because Panel A makes it difficult to discern the difference between the two series, Figure 4, Panel B captures a scatter plot of these values. These results are encouraging, since the corresponding values cluster around a line through the origin with slope equal to one.

Clearly this proof of concept is artificial—albeit realistic—since all assets are not available for investment during the entire period. This scenario contains look-ahead bias since we estimate the coefficients using all information available in the sample. Realistically, at any given point in time, we could only estimate the relevant betas using past information instead of across the entire time period as shown here. Additionally, this proof of concept does not allow for dynamic factor models that might provide additional insight. We incorporate a form of conditioning factor model where portfolio weights change with the "state-of-the-world" in the future real-world applications. With these considerations in mind and with the belief the GA works as intended, we now turn to out-of-sample testing using an actual target and investable assets.

Applying the GA to Health Care Risk Exposure

In this more realistic application of the GA, the objective is to minimize the variance of a hedged portfolio consisting of a short position in medical inflation and a long position in a portfolio of assets. A zero variance hedged portfolio indicates perfect correlation between the target and hedging portfolio. While such a portfolio would be ideal from the hedging standpoint, from a risk management standpoint it is also reasonable to allow for a hedging portfolio that allows for superior first and second moments of the hedged portfolio even if it does not correlate perfectly with the target. In other words, we contend that if a hedged portfolio of assets provides a higher mean and lower variance out-of-sample than simple exposure to the target it intends to hedge, while it might not covary perfectly with the target and induce a low hedged portfolio variance, such a portfolio nevertheless represents an effective risk management mechanism from a

funding standpoint. We subsequently provide a more tangible explanation of this argument.

In this real-world exploration, the choice variables that accomplish the objective are a set of five assets chosen from a universe of 306 assets. The 306 assets include 303 stocks pulled from CRSP that have returns as of January 1967 and December 2008, which is the period for which we have relevant medical inflation data. Additionally, these stocks have uninterrupted return data for at least 100 months before 2005, which is the earliest out-of-sample period we consider for the macroeconomic series. We also include three government bond monthly return series: the 10-year bond, one-year note, and 30-day bill. Clearly all of these assets are truly "investable" leading up to the out-of-sample periods in a practical sense, unlike those shown in the proof of concept scenarios. Further, the results shown are but a starting point considering the recent work of Brandt and Santa-Clara (2006). These authors show that applying conditioning and timing methods to asset returns can expand the asset universe essentially without bound. While we consider conditioned returns for our mutual fund and exchange-traded fund (ETF) applications, we do not incorporate timing methods here.

Broadly speaking, the problem at hand can be characterized as follows. Starting today, you have a known liability (assuming medical prices remain constant) over the next year resulting from medical expenses. We are assuming no "quantity" risk in this medical expense. That is, we assume the level of medical services remains constant, and the only uncertainty comes from medical price changes. Given that medical expenses are likely to increase in an uncertain fashion (see Figure 1), you need to invest in a set of assets that will increase in value at or above the rate of medical inflation, and at the same

time result in a combined net asset position that has volatility lower than if the medical liability were hedged with risk-free investments. Such “risk-free” investments (e.g., government bonds or CDs) basically represent the “baseline” hedging strategy since it is unlikely an exposed entity would let available funds sit idle and bear no interest.

Panels A through C in Figure 5 depict relevant scenarios. With return on the y-axis and time on the x-axis, Short Target represents a short position in the series (e.g., medical inflation) you wish to hedge. In Panel A, the ideal Hedging Portfolio would mirror the Short Target series exactly, leading to the ideal Hedged Portfolio, which in this example has zero variance. To the extent this Hedged Portfolio lies above or below the zero return line, it is possible to hedge the target using more or less funds than the known liability. Specifically, the Hedged Portfolio in Panel A indicates a hedging portfolio with a mean periodic return higher than that of the target series, which means you could invest less than the current known liability and still offset the future liability exactly. Thus Panel A is an ideal scenario: a hedged position that is less risky than a natural short position along with a fully-funded (in fact over-funded) liability. Panel B depicts a scenario where a constant return asset such as a T-Bill serves as the Hedging Portfolio. Clearly the Hedged Portfolio exhibits higher return variance than in Panel A, and in this case the variance ratio of the hedged portfolio to the target series equals one since the variance of the Hedged Portfolio equals the variance of the Short Target. Although we show a situation where the constant return of the Hedging Portfolio is greater than the absolute value of the Short Target return, if this constant return series were less than the absolute value of the Short Target return, then we would have a situation where the liability would be underfunded over time. Thus it is important to consider both the

variance ratio and return levels when considering the hedging portfolios' effectiveness from a risk management standpoint. Finally, Panel C depicts a more real-world scenario where the Hedging Portfolio correlates with the Target with an absolute value between zero and one. In this case, the Hedging Portfolio relationship with the Short Target series creates a Hedged Portfolio with higher variance than the Short Target position. However, the liability is always fully-funded since the returns to the Hedged Portfolio are non-negative. It is straightforward to envision the alternative scenario whereby the Hedged Portfolio variance is lower than the Short Target with negative returns.

Returning to our GA, the objective in this case it to choose five assets, (i, j, k , l, and m) from 306 assets without replacement and weight them to form a hedging portfolio with return $Portfolio_t$ according to equation (4),

$$Portfolio_t = a_0 + a_1Ret(i) + a_2Ret(j) + a_3Ret(k) + a_4Ret(l) + a_5Ret(m) \quad (4)$$

where $Ret(x)$, represents the return on a particular asset and $i...m$ are the indices that indicate one of the 306 assets. $a_1..a_5$ are hedge ratios determined by OLS regression. We next define the hedged position, or hedged portfolio, as H_t in equation (5).

$$H_t = Portfolio_t - CPIMEDMO_t \quad (5)$$

Here, $CPIMEDMO_t$ serves as the medical inflation target we are trying to hedge and $Portfolio_t$ is the return series of the hedging portfolio which consists of five investable assets and is shown fully in equation (4). Since we are naturally short the medical inflation position in that we must pay medical care costs each time period, we take a long position in $Portfolio_t$ to offset the movements in $CPIMEDMO_t$, which will ideally stabilize H_t and minimize the risk of escalating health care costs. H_t is analogous to the $Error_t$ series in equation (1).

In evaluating the hedging portfolio's fitness, we again randomly generate 1,000 candidate hedge portfolios consisting of five "genes", or assets, and define this set as the initial population. To evaluate the performance out-of-sample, we divide the data into three regions as shown in Figure 6. For our baseline analysis, these periods include the Test period (January 1967 to December 2006), Validation period (January to December 2007), and the Out-of-Sample period (January to December 2008). For robustness purposes we also explore calendar years 2005-2007 as out-of-sample periods. We then regress medical inflation ($CPIMEDMO_t$) on these assets according to Equation (6) using *only* the data in the "Test" period. Equation (6) shows an example form of this regression using assets 1, 7, 25, 36, and 41.

$$Portfolio_t = a_0 + a_1 Ret(1) + a_2 Ret(7) + a_3 Ret(25) + a_4 Ret(36) + a_5 Ret(41) \quad (6)$$

From this regression come estimates for the hedge ratios $\hat{a}_0 \; .... \hat{a}_5$. Using these parameters, it is possible to calculate the time series for $Portfolio_t$ over the "Test" period per equation (4) and continue using the hedge ratios through the "Validation" period. Since the "Validation" period is outside the range used to estimate the parameters, it accounts for performance of the model formed during the "Test" period in a pre-out-of-sample manner and reduces the criticism of overfitting the model based on past known information. Next we calculate the mean and variance of H_t, $Portfolio_t$, and $CPIMEDMO_t$ for both the "Test" and "Validation" periods. The fitness level in this application, which we seek to minimize, consists of a weighted measure that accounts for these attributes as shown in equation (7),

$$Fitness = w_1 \sigma^2_{H,Test} + w_2 \left(\frac{\sigma^2_{H,Validation}}{\sigma^2_{H,Test}} \right) \quad (7)$$

where $\sigma_{x,y}^2$ is the variance of return series x during period y. Using the two terms incorporates the variance of the hedged portfolio in both the Test and Validation periods. Specifically, the first term simply measures the variance of the hedged portfolio, H, weighted by factor w_1. The second term expresses the idea that it is desirable for the variance of the hedged portfolio in the Validation period to remain consistent with or lower that it is in the Test period. We consider it a stability measure and weight its importance by w_2. To emphasize, in this construct lower fitness values are preferred.

Initially we set (w_1, w_2) to (1, 1) but also complete sensitivity checks using other weight vector values. We repeat regression (6) and calculate the fitness using equation (7) for all 1,000 candidate solutions in the initial population. Having initialized the candidate solution population, we use the iterative GA procedure, or breeding, as described in the proof of concept above to evolve an improved solution over multiple generations. The major differences between this real-world application and our earlier proof of concept involve the set of possible hedging assets and the fitness level measure. The breeding process and its user-defined inputs (e.g., number of genes, number of parents, breeding population, mutation procedure, and crossover rate) remain consistent with the proof of concept.

Results

Table 2 shows the generation-by-generation results of a GA run with the fitness weights (w_1, w_2) set to (1, 1). The generation-by-generation population minimum, mean, and maximum fitness measures vary as anticipated. The minimum decreases over time, the maximum fluctuates randomly given our allowance for mutations, and the mean also

fluctuates, but to a lesser degree. Again, we calculate these fitness measures using Equation (7). The final column shows the mean fitness measure for only the breeding population, which are the top 100-performing portfolios in each generation. As expected, again the minimum fitness values decrease (Column 2), or improve, over generations until convergence in the tenth generation. In this case, we again notice two things about the mean fit of the breeding population (Column 5). While its fitness value steadily improves (i.e., decreases) asymptotically over time, the breeding population has not converged to the minimum value shown in Column 2. Thus it is theoretically possible to obtain even better performance if we were to allow for additional generations, and the possibility of mutations always makes this possibility hold. However, improvement seems improbable given the best existing solution in most cases is a unique one. This "most fit" member is often just one member in a 100-member breeding population, and since we allow pairings to occur randomly (as opposed to forcing this "most fit" solution to breed each generation), is no more likely to "breed" than any of the other breeding members.

Performing a brief sensitivity analysis by varying (w_1, w_2) leads to Table 3. Clearly there are many more possibilities than those shown, but the point is merely to demonstrate the potential for the GA to generate nice solutions. Column 1 shows varying weight values, while Column 2 depicts the ratio of the variance of the hedged portfolio to the variance of actual medical inflation for the out-of-sample evaluation. Columns 3 through 7 depict the assets that compose the best hedge portfolio as determined by the GA; the Asset Key table at bottom shows the associated CRSP tickers for these assets. Appendix C lists all asset-ticker-industry combinations for the GA-generated portfolios

for the rest of this study. Column 8 shows the generation at which the minimum fitness level converges for each respective weight combination. In the analysis to date, we constrain the process to end after 10 generations. The final column shows the mean out-of-sample excess monthly return by investing in the hedging portfolio. For instance, by investing in stocks 274, 79, 199, 33, and 214,[16] (i.e., weight vector (1,1)) and simultaneously remaining naturally short the medical inflation measure, one would earn an average return of 0.316 percent per month on hedged portfolio between January and December 2008, indicating the liability is fully-funded as described earlier. And since the mean fitness level of the breeding population has not yet converged to the minimum value in virtually any of these cases (not shown), again it is theoretically possible that an even better solution exists than shown here. Of course, mutations could always improve the population even after convergence.

For this relatively small sample of weight values, Column 2 of Table 3 (which quantifies the variance ratio between the hedge portfolio and medical inflation) indicates that the GA-determined hedge portfolio eliminates up to 49 percent (i.e., ratio equals 0.51) of the variance in medical inflation for the out-of-sample period. That is, the variance of simultaneously having a short position in medical inflation and a long position in the five GA-selected stocks and/or bonds generates a portfolio variance less than one-half of what it would be simply remaining exposed to the medical inflation series. In this "best" case, the portfolio consists of four stocks[17] and the 30-day Treasury Bill, which is represented by return series 306. Figure 7, Panels A through C depict the

[16] The major industries of the stocks that correspond to these index numbers are Processed & Packaged Goods, Entertainment, Specialty Retail, Security & Protection Services, and Industrial Equipment.
[17] The stock industries include Accident & Health Insurance, Restaurants, Rental & Leasing Services, and Domestic Telecommunication.

out-of-sample return series and assets' relative weights within the hedging portfolio, respectively. Clearly for the weight vector (1,0) portfolio, a long position in the T-Bill dominates the position, with an investor holding very small positions in the other 4 assets, which are stocks. Notably, however, even these small positions affect the portfolio's overall return series non-trivially. This effect becomes evident by comparing this portfolio's variance ratio of 0.51 to a ratio of 0.995 when using only the T-bill as a hedging portfolio. We discuss this T-bill situation in more detail below. The other two portfolios consist solely of a set of common stocks. Clearly the performance is sensitive to the weight values, and even in the "worst" case depicted (i.e., (0,1)), the variance of the hedged portfolio is still below unity at 0.97. While the variance ratios are appealing, perhaps as relevant from a broader risk management perspective is that in each hedged portfolio the monthly returns on average dominate the rise in medical inflation, and in every case these hedging portfolio returns are greater every month (see Figure 7 and its subsequent explanation for the graphical evidence). Thus while the portfolio might not always track the target of medical inflation precisely, investing in a GA-selected portfolio of five common stocks and government bonds appears to offset the rise in health care costs in the out-of-sample period studied here, while simultaneously lowering the liable entity's risk exposure.

Knowing the sensitivity to the weights, we must select a set of weights for further analysis and application. While (1,0) appears to be the "best" result from Table 3, we are concerned this set of weights fails to account for the Validation period results and the associated performance stability we desire and described earlier. The weight vector (1,1) is also appealing, since its hedged portfolio reduces the risk of exposure to medical care

costs by approximately 14 percent. However, since the weight vector (0,1) also provides convincing results (i.e., variance ratio is less than one and the mean monthly return of the hedged portfolio is positive), it seems to present the most conservative yet still effective case. Therefore we select the vector (0,1) for analysis from here forward. We label this weight vector (0,1) the "good" case—as opposed to the "better" or "best" case—going forward. Making this selection provides us with an effective hedge for medical inflation since the variance ratio is less than one, allows us to account for both the Test and Validation period data, and hopefully forestalls allegations that we are "cherry-picking" for the best subsequent results.

To expand a bit on this weight set using Figure 7, it is visually difficult to discern that the hedge portfolio, *H*, has lower variance than medical inflation, since the ratio is close to unity. However, it is clear the monthly returns for the hedging portfolio for the "good" case (RETHEDGEPORT) outpace medical inflation. In other words, investing in this hedging portfolio of assets 81, 76, 84, 229, and 117[18] covers a firm's medical inflation exposure and on average provides a mean monthly excess return of 0.328 percent (or roughly 4 percent annually) during the out-of-sample period over medical inflation.

While we introduce the significance of excess mean return in the discussion surrounding Figure 5, Table 4 quantifies what this excess return means for the entity seeking to fund a future liability for the year 2008. Assuming an entity is setting aside $1 million to fund the anticipated medical care expense it will incur sometime during 2008, Column 2 shows monthly medical inflation, with Column 3 showing what the $1 million

---

[18] The stock industries include Chemicals, Business Equipment, Electric Utilities, Manufacturing, and Steel & Iron. Appendix A lists the stock index numbers, tickers, and industries.

liability would cost if incurred at the end of the associated month. Column 4 shows the monthly hedging portfolio return using assets 81, 76, 84, 229, and 117 (see Figure 7, Panel B), and Column 5 translates these returns into dollar values if the $1 million set-aside is invested in the hedging portfolio. Column 6 shows how much of the original $1 million would have been needed to offset the liability exactly, with Column 7 (8) showing the excess initial funds (as a percentage) at the beginning of the year if the whole liability were to occur at the end of the associated month. The range of "excess" funds at the outset is between 0.09 percent and 3.93 percent in this example. Again, this overfunding occurs due to the hedging portfolio returns outpacing medical inflation every month of 2008, and the GA finds an investment portfolio that creates less risk for the exposed entity than doing nothing and remaining exposed to medical inflation. And while a portfolio of all stocks like the one with weight vector (0,1) perhaps creates more risk than simply investing in T-bills, using T-bills requires investing all of the liable funds in this single asset. A shock to the one-to-one relationship between medical inflation and T-bills could be devastating for the liable entity, whereas a portfolio of multiple (e.g., five) assets could more easily absorb a shock to the relationship between one of its assets and the medical inflation target, not to mention the inferior performance of the T-bill as a lone hedging asset discussed in the subsequent paragraph. Additionally, while the all-stock portfolio with weight (0,1) is inferior from a volatility standpoint, it is possible that the excess mean return compensates for this loss.

Figure 8, Panel A, depicts the potential portfolios in mean-standard deviation space. Clearly all three of the hedged positions dominate a short position in medical inflation ("Med Inf") with both a higher mean and lower standard deviation in their out-

of-sample returns, and it appears the hedging portfolio with weights (0,1) is slightly inferior to (1,1), again confirming it as the conservative choice going forward. Finally, since the question naturally occurs, untabulated analysis shows simply taking a long position in T-bills provides a slightly inferior variance ratio of 0.995 but also means an average return deficit of 0.22 percent per month in 2008. In other words, simply investing in T-bills is (slightly) more risky than the GA-generated hedging portfolio while also leaving the entity underfunded for the year.

Another natural question that arises concerns the effectiveness of the S&P 500 as a hedge for medical inflation. Intuitively, since medical inflation has generally been positive since the 1970s (Figure 1) and the S&P 500 index has also tended to grow over time, one might think these two trends might correlate well. Contrary to this intuition, investing in the S&P 500 would serve as a relatively poor hedge for medical inflation when considering the GA-generated portfolios. Taking a long position in the S&P 500 does not serve as an effective hedge for medical inflation in terms of its variance ratio. Respectively, for calendar years 2005, 2006, 2007, and 2008, the variance ratios of the hedged portfolio (i.e. long S&P 500; short medical inflation) to the medical inflation target series are 271.04 , 232.25, 380.67, and 4,203.12. The respective correlations between the S&P 500 monthly return series and monthly medical inflation of 0.21, -0.40, -0.13, and -0.19 for 2005 to 2008 also provide weak support for using the S&P 500 to hedge medical inflation. Finally, using the S&P 500 not only makes the hedged portfolio more risky but also fails to manage risk from the standpoint of funding the medical liability. In 2005, 2007, and 2008, the average monthly returns of a hedged portfolio

consisting of a long position in the S&P 500 are negative (-0.11, -0.13, and -4.27 percent, respectively).

Returning to the "good" portfolio resulting from the GA, it is further possible to generate the parameters in equation (4) to see the out-of-sample hedge ratios for assets that form the hedging portfolio. Table 4 shows these results for the Test period according to equation (7). As an aside, the relative weights in Figure 7, Panel B come from normalizing these regression parameters (i.e., dividing each individual parameter by the sum).

$$CPIMEDMO_t = \beta_1 + \beta_2 \cdot Ret(81)_t + \beta_3 \cdot Ret(76)_t + \beta_4 \cdot Ret(84)_t + \beta_5 \cdot Ret(229)_t + \beta_6 \cdot Ret(117)_t + v_t \quad (7)$$

In this model, the $Ret(x)$ labels refer to the monthly security returns for stock x as described earlier. Table 4 indicates hedge ratios on the individual assets are statistically insignificant at conventional levels. However, this statistical insignificance during the Test Period becomes less relevant when we consider that our ultimate concern is the out-of-sample performance.

Two natural concerns with implementing this method are transactions costs and the ability to take short positions in the required assets. Since in this application the hedging portfolio is formed at the beginning of the out-of-sample calendar year and frozen for the rest of the year, transactions costs occur once. Therefore, since portfolio turnover is almost nonexistent, we do not account for transactions costs in our macroeconomic examples. However, in foreshadowing, the mutual fund and ETF extensions in this paper exhibit greater turnover and do account for such transaction costs. Regarding short sale constraints, for this version of the paper, we proceed in the spirit of Brandt and Santa-Clara (2006), who also exhibit optimal portfolios consisting of

short positions in both stocks and bonds. At an applied level, clearly short sales must be dealt with by the practitioner on an asset-by-asset basis. Potential future work involves altering the fitness function to avoid any short positions.

Finally, to put these findings into graphical perspective and relate them to past work, Figure 8, Panel B compares the possible medical inflation hedging scenarios in the mean/standard deviation space. Knowing the hedged position for the all GA-generated cases dominates the natural short position in both the first and second moments from Panel A, Panel B presents a relative comparison of the GA hedging portfolios' performance to the health care mutual funds in the spirit of Jennings, Fraser, and Payne (2009). Clearly the GA hedging portfolio performs superior to the intuitive natural hedges represented by the health care-related mutual funds offered by Eaton Vance, Vanguard, and Fidelity (ETHSX, VGHCX, and FSPHX, respectively).

Extended Applications: Out-of-Sample Robustness Analysis, Other Macroeconomic Series, and Investable Assets

Out-of-Sample Robustness and Other Macroeconomic Series

Having demonstrated the GA's ability to find an effective investable hedging portfolio for medical inflation that is also a better hedge than health care-related mutual funds using calendar year 2008 as the out-of-sample period, the natural follow-up question is its ability to provide good solutions for a more robust set of timeframes as well as for other uninvestable macroeconomic series, such as some of the 17 series analyzed in Flannery and Protopapadakis (2002). Additionally, one wonders whether this GA technique could perhaps find a parsimonious or better-performing portfolio relative

to investable assets such as stock indexes, mutual funds, or exchange-traded funds (ETFs). As the following results show, while the GA performance does not universally reduce the risk as measured by portfolio variance, it gains appeal when considering the mean return provided to offset this (sometimes very slight) additional risk. Finally, the GA-developed portfolios perform quite well out-of-sample when “mimicking” other investable assets such as mutual funds and ETFs.

The prior results surrounding medical inflation invite the criticism of look-ahead bias. While up to this point we have chosen a fitness measure weight vector retrospectively based on out-of-sample performance that has already occurred, to strengthen the argument for applying this GA procedure requires selecting a fitness measure a priori without the foresight of which (w_1, w_2) weight vector is best. As discussed and decided upon earlier, we run all future results with and only with (w_1, w_2) equal to (0,1), which we call the “good” case and one could argue is conservative since it does not provide the “best” out-of-sample hedging portfolio for medical inflation. Making this decision in advance represents the situation we would face in a real-world application.

We select macroeconomic series based on practical relevance as well as data availability. Not all target series are available beginning in January 1967; we note the available dates for each series parenthetically in future descriptions. Additionally, we think the results presented could be conservative for a reason beyond the fitness weight vector. While some target series begin in, say, the mid-1980s, we do not expand the investable stocks available to hedge the particular series to those that have returns beginning in the mid-1980s and continuing until the present. So while we constrain the

number of available assets in the hedging portfolios at one level, on another level we allow them to expand. As Brandt and Santa-Clara (2006) highlight, we could include conditional assets to expand the set available almost infinitely. To foreshadow, we do increase the available assets in the mutual fund and ETF analyses by incorporating a conditioning variable (see Cochrane (1996)), but doing so comes with a price, as altering the portfolio more often than annually increases transaction costs. We account for these costs in this analysis.

One rationale for using this GA technique to hedge other macroeconomic series could be for insurers to hedge the payouts to claimants, particularly for homeowners policies. Since various macroeconomic series might best capture these liabilities, we look at a host of possibilities, including the housing component of inflation (January 1967 to December 2008), the Case-Shiller 10-City Composite Housing Price Index (January 1987 to December 2008), and the Producer Price Index for Residential Construction (June 1986 to December 2008). The first and last series come from FRED, and the Case-Shiller Index data comes from the Standard and Poor's website.[19]

From a transportation and energy perspective, there could be multiple uses for an investment portfolio to hedge associated liabilities such as fuel prices. For this reason, we apply the GA to the energy component of inflation (January 1967 to December 2008), transportation inflation (January 1967 to December 2008), spot oil price for a barrel of West Texas Intermediate (January 1967 to December 2008), spot price for a gallon of New York Harbor kerosene-type jet fuel (April 1990 to December 2008), and monthly price per gallon for diesel fuel (March 1994 to December 2008). FRED provides data on

[19] http://www.standardandpoors.com/indices/sp-case-shiller-home-price-indices/en/us/?indexId=spusa-cashpidff--p-us----

the inflation measures, Dow Jones provides information on the spot oil prices, and the Department of Energy is the source for both jet and diesel fuel prices.

Last, but certainly not least, two macroeconomic series of general interest include aggregate inflation and changes in the S&P 500 index. Bodie (1976) investigated the question of hedging aggregate inflation, so this question is not new, and our GA-generated results support his conclusion that shorting common stocks is an effective hedge for inflation. However, the GA in this paper tells us exactly *which* five stocks do an effective job. While we anticipate the GA will find a set of five stocks that will generally track the S&P 500 index, we do not believe it will be easy for such a portfolio to have lower variance given the Statman (1987) finding that well-diversified portfolios require 30 to 40 stocks as opposed to the five we select using this GA. Finally, from a time series econometrics standpoint, since all of these data series mentioned are captured in levels, we difference the natural log values between periods to convert them into returns to correspond with the return values for the hedge portfolios as well as move from non-stationary to stationary time series.

The results of the GA's performance for these various macroeconomic series are shown in Table 6. Panels A through D of Table 6 depict 4 calendar years' worth of out-of-sample results. The Panels are in reverse chronological order so we can view more recent out-of-sample results first. We use the calendar years 2005 to 2008 to capture recent results across a range of economic climates, with the earliest 2 years (2005-2006) showing evidence of economic growth as measured by the S&P 500, followed by a relatively "flat" year in 2007, and ending with the obviously challenging economy in the year 2008.

Overall, these results show that selecting a set of five investable assets to hedge various macroeconomic phenomena is imperfect, which supports the Chen, Roll, and Ross (1986) finding that the first-pass Fama-MacBeth (1973) regressions of macroeconomic factors on stock portfolios do not perform very well, but it is not impossible. The best variance ratios occur with the S&P 500, the only series having ratios of less than unity across all time periods. It has variance ratios ranging from 0.62 to 0.87, which indicates the GA-identified hedged positions reduce variance by 13 to 38 percent. Additionally, the S&P hedged portfolio provides positive mean monthly returns for the most recent two years studied, 2007 and 2008, indicating that perhaps the GA technique is most effective in flat or downward-moving markets. Globally, the worst variance ratio is the 2008 Case-Shiller 10-City Composite Index, where the GA-generated hedged portfolio is 29 percent more volatile than the Case-Shiller Index.

Looking at medical inflation, the GA portfolios perform well in our estimation. In both 2007 and 2008, the variance ratios of the hedged portfolio is lower than 1.0, and the worst variance ratio occurs in 2006 at 1.07. Nevertheless, in every case the entity embracing the hedging portfolio is fully funded out-of-sample, with monthly (annual) excess returns ranging from 0.13 (1.58) percent in 2007 to 0.33 (4.01) percent in 2008. From a mean-standard deviation perspective, the hedging portfolios in 2007 and 2008 provide an unambiguously better position for the exposed entity. The Pearson correlations between medical inflation and the hedging portfolio presented in Column 5 provide mixed results; the positive values in 2007 and 2008 are desirable, but the negative correlations in 2005 and 2006 are concerning. The 2005 and 2006 results indicate at worst the entity must seriously consider the tradeoff between risk and return,

since with slightly more risk it can clearly fund the health care liability. In no case is the GA-generated hedging portfolio unambiguously worse (i.e., higher variance and lower return).

The housing-related series tend to provide mixed results over time. As a whole, the variance ratios are better during the economic growth years of 2005 and 2006 with 2 of the 3 series having ratios below 1.0 in each year (housing inflation and Case-Shiller in 2005; Case-Shiller and PPI residential construction in 2006). However, from the perspective of fully-funding the liability, the latter years of 2007 and 2008 provide better risk management portfolios with positive mean monthly returns to the hedge portfolios for both housing inflation and the Case-Shiller Index. The target-hedging portfolio correlations are positive for PPI residential construction in all years except 2008, but no clearly apparent trends emerge for the other series over time or based on the economic environment.

The energy and transportation area includes five series that provide mixed results in terms of hedging effectiveness. Approximately one-half of the series-year combinations show reduced risk from taking the hedged position, since 11 of the 20 combinations exhibit variance ratios under 1.0, and exactly 10 of the 20 series-year combinations indicate the hedged portfolio fully funds the liability. While in the difficult economic environment of 2008 all hedged portfolios are slightly more volatile than the target with variance ratios ranging from 1.01 (energy inflation, transportation inflation, and diesel fuel PPG) to 1.13 (jet fuel spot price), all of the liabilities are overfunded based on the positive mean monthly returns to the hedged portfolios. At the opposite extreme, in 2005, all variance ratios are less than one, ranging from 0.86 (jet fuel spot price) to

0.99 (energy inflation and diesel fuel PPG), but the hedged portfolios exhibit negative mean monthly returns in all but one case (transportation inflation). Additionally, as a group the positive correlations between the target and hedging portfolios are more appealing for the year 2005 than for 2008. In the more flat economic period of 2007, a hedged position would reduce risk in four of five cases, with transportation inflation representing the exception, but the hedging portfolio would underfund the liability in every case. During the economic growth year of 2006, hedging performance is noteworthy for both the oil spot price and transportation inflation, as both exhibit risk-reducing hedged portfolios that would fully fund the associated liability. All things considered, it appears the GA hedging portfolios' effectiveness in addressing energy/transportation-related risk is sensitive to the economic environment, with the slightly more effective results appearing to come during difficult economic environments like the one that occurred in calendar year 2008.

Finally, with the other two series of interest, aggregate inflation and the S&P 500 return series, hedging performance generally appears solid across all periods. For aggregate inflation, the hedged portfolio fully funds the liability in every year studied. Both 2008 and 2005 are years where the benefit of the hedging portfolio is unambiguous, since besides having mean excess returns, in these years taking the long position in the hedging portfolio reduces the volatility of the return series. While the correlations could certainly be higher, with the maximum (minimum) correlation of 0.23 (0.02) occurring in 2005 (2006), it is encouraging they are non-negative for all out-of-sample years. For the S&P 500, as previously mentioned, it is the only macroeconomic series studied where the hedged portfolio exhibits less volatility than the target in every year. Again, the concern

is certainly the underfunding that occurs out-of-sample during the economic growth years of 2005 and 2006. This concern is somewhat mitigated by the correlations between the target and the five-stock hedging portfolio, which range from 0.38 in 2007 to 0.70 in 2008. Oddly enough, of all the macroeconomic series investigated here, the only two containing a bond in the GA-generated hedging portfolio are the energy inflation in 2006 and the S&P 500 in 2005. Untabulated results show this short (one-year) bond composes over 99 percent of these portfolios, with the energy inflation hedge consisting of a short position in the bond and the S&P 500 consisting of a long position.

Other Investable Assets: Mutual Funds and Exchange Traded Funds (ETFs)

The recent S&P 500 results encourage us to expand our analysis further regarding the GA performance for investable assets. In 2008, the five stocks found by the GA create a hedged portfolio that is approximately 40 percent less risky than the S&P 500 while exhibiting a mean out-of-sample monthly (annual) return of 3.38 percent (49.10 percent). While one might be concerned this performance occurs in 2008, a notoriously poor market, we are encouraged the GA finds good solutions exactly when investors need them. Again, these GA-generated hedging portfolios consist of stocks listed on the major US exchanges, not more speculative assets such as derivatives, which would surely have higher expected returns but also likely higher risk. If an industry such as insurance were to invest according to these results, regulators would more likely raise issues if the hedging assets for medical inflation consist of corn or soybean futures than common stocks.

From an investment standpoint, the S&P results indicate the potential for the GA to find appealing investment tracking portfolios. Specifically, the S&P results force us to investigate whether the GA can find a portfolio of five stocks that track a mutual fund or ETF with perhaps either less return variance and/or higher mean returns out-of-sample. To perform an initial exploration of this question, we randomly select ten mutual fund series with varying return history lengths and run the GA using these funds as respective targets. As with the macroeconomic series, we keep the weight vector (w_1, w_2) equal to (0,1) to avoid any look-ahead bias. These funds include those with ticker symbols ACMVX (April 2004 to December 2008), BRGIX (December 1998 to December 2008), EXOSX (July 2002 to December 2008), EXTAX (April 1998 to December 2008), FBALX (January 1987 to December 2008), FCNTX (May 1989 to December 2008), FDVLX (July 1989 to December 2008), JMCVX (September 1998 to December 2008), SPHIX (November 1994 to December 2008), and WAGTX (January 2001 to December 2008). We list the funds and their associated Morningstar style boxes in Figure 9.[20]

The major difference between the mutual fund and prior macroeconomic series analysis involves the use of conditional weighting on our hedging assets. Cochrane (1996) demonstrates the relevance of using returns that are conditioned on some state variable, and Brandt and Santa-Clara (2006) discuss how doing so greatly increases the effective assets under consideration. As we discuss later, doing so comes with the transactions costs imposed by frequent rebalancing.

In this case we condition the hedging asset weights on the predicted value of the mutual fund under consideration. To summarize the problem, the objective in this case is

[20] Collected from http://finance.yahoo.com/

to choose five assets, (i, j, k, l, and m) from 306 assets without replacement and weight them to form a hedging portfolio according to equation (8).

$$Portfolio_t = a_0 + a_1 Ret(i) + a_2 Ret(j) + a_3 Ret(k) + a_4 Ret(l) + a_5 Ret(m)$$
$$+ b_1 Ret(i) Cond_t + b_2 Ret(j) Cond_t + b_3 Ret(k) Cond_t + b_4 Ret(l) Cond_t + b_5 Ret(m) Cond_t \quad (8)$$

where $Ret(x)$, represents the return on a particular asset and $i \ldots m$ are the indices that indicate one of the 306 assets. $a_1 \ldots a_5$ and $b_1 \ldots b_5$ are hedge ratios determined by OLS regression. $Cond_t$ is a conditioning variable, which is the best predicted mutual fund return we can get from a stepwise regression across the "Test" period that includes 3 months' lagged values of the mutual fund, the market return net of the risk-free rate, the S&P 500 return, inflation, the long government bond return, short government bond return, and 30-day Treasury Bill returns. In other words, the conditioning variable is formed only using past information that is readily available to predict the future fund return. Notationally, the stepwise regressions include the aforementioned variables at time t-k, where $1 \leq k \leq 3$. While data mining is clearly a criticism of this specific technique, the practical goal of this step is to generate the best forecast for the respective mutual fund using all relevant information available. The resulting conditioning variable and estimation equation varies by fund, but for example, the conditioning variable for fund ACMVX looks like equation (9),

$$Cond_t = \widehat{ACMVX}_t = \hat{\alpha}_0 + \hat{\alpha}_1 ACMVX_{t-3} + \hat{\alpha}_2 MKTRF_{t-3} + \hat{\alpha}_3 B10Ret_{t-2} \quad (9)$$

where $ACMVX_t$ represents the fund return for month t, $MKTRF$ is the market return minus the risk-free rate, and $B10Ret_t$ is the 10-year government bond return for month t. This conditioning variable allows the hedge ratios on the individual assets to change with

the state-of-the-world as suggested in Cochrane (1996). As before, we next define the hedged position, or hedged portfolio, as H_t in equation (10).

$$H_t = Portfolio_t - ACMVX_t \quad (10)$$

In evaluating the hedge fitness, we again randomly generate 1,000 candidate hedge portfolios consisting of five "genes" each and define this set as the initial population. We use the same Test, Validation, and Out-of-Sample periods discussed previously. We regress the mutual fund target series ($ACMVX_t$) on these assets and their conditioned variables according to Equation (8) using *only* the data in the "Test" period.

Results for these mutual fund targets are found in Table 7 for the out-of-sample period calendar year 2008. From the top-level, the GA finds hedged portfolios (i.e., short position in mutual fund and long position in hedging portfolio of five stocks) that reduce the variance of simple exposure to the mutual fund in 7 of 10 cases (i.e., EXOSX, FDVLX, and WAGTX are the exceptions). In the 7 "successful" cases, taking positions in the hedged portfolios reduces risk exposure (i.e., variance) by anywhere from about 5 to 57 percent. In the three cases where hedged positions exacerbate the risk, the increase in risk ranges from 6 to 47 percent. Notably, however, for these three funds, the excess return of holding the hedged position is non-trivial, ranging from 4.61 (71.77) to 8.94 (179.32) percent monthly (annually). Thus the higher risk begets higher returns in these cases. In the 7 other cases, the hedging portfolio unambiguously improves the investor's situation in that it creates a scenario with less risk and higher returns, ranging from on average 2.23 (30.31) to 3.64 (53.49) percent monthly (annually). For all cases the correlation between the target fund and hedging portfolio is above zero (see Column 9). As we note in Table 7, in the cases of BRGIX and EXTAX the stepwise prediction regression finds no variables that performed well in predicting future returns to these

funds. Thus the out-of-sample investments in the hedging portfolios for these two funds are fixed for the entire out-of-sample period, just as they are for the prior macroeconomic target series.

To emphasize the point that the GA-generated solutions are unambiguously better, we look at adjusting the hedging portfolios for risk using both the Sharpe ratio and Jensen's alpha. Because it is practically difficult to take a short position in a mutual fund per se without simply shorting each stock in the fund, our risk-adjusted comparisons juxtapose the GA-generated hedging portfolio with the target mutual fund. Columns 5 and 6 of Table 7 quantify the Sharpe ratios for both the hedging portfolio and the target. The shaded values indicate which series has the higher Sharpe ratio, and in every case the GA-generated portfolios offer greater returns out-of-sample for each unit of risk (as measured by standard deviation). We emphasize this point using Figure 9, Panel A, which depicts the out-of-sample alternatives for an investor: (1) either invest in ACMVX or one of the other 9 funds or (2) invest in the GA-generated five-stock portfolio alternative or counterpart, labeled "(A) ACMVX" or "(A) xxxxx," where xxxxx represents the ticker for one of the other nine funds. The arrows on this plot originate at the target fund and proceed to the GA-generated five-asset portfolio. For example, the circled points indicate alternative (1) above, which is to invest in ACMVX, connected with alternative (2), which is to invest in the GA-generated "mimicking" five-asset portfolio, or (A) ACMVX. Since most investors with typical mean-variance preferences would desire higher return and lower risk, it is clear (A) ACMVX presents both for this out-of-sample period. Beyond this specific example, in all but one case, the "northwest" direction of the arrows unambiguously indicates the GA-generated portfolio provides

dominant first and second moments. The lone “northeast” arrow (i.e., fund WAGTX) presents a scenario where an investor must make a judgment call based on risk preferences over the mean and standard deviation of returns. Notably, if one were able to short the fund and go long the GA-generated portfolio, the results would become stronger than depicted.

As mentioned before, one clear consideration when opting for the GA-generated five-asset portfolio is transaction costs. While the investing policy (possibly) changes annually, the conditional nature of the hedging portfolio means its composition likely changes monthly based on updated predictions about the target series according to equation (11), which is simply equation (8) re-arranged to group terms associated with each asset i, j, k, l, and m.

$$Portfolio_t = a_0 + (a_1 + b_1 Cond_t)Ret(i) + (a_2 + b_2 Cond_t)Ret(j) + (a_3 + b_3 Cond_t)Ret(k) + (a_4 + b_4 Cond_t)Ret(l) + (a_5 + b_5 Cond_t)Ret(m)$$

The weight placed on each asset varies with the state-of-the-world, $Cond_t$, or the predicted value of the fund described with equation (9). As a result, each of the five securities in the hedging portfolio is likely traded monthly to establish the optimal position going forward. Thus the transactions costs will impact the return to the hedging portfolio. Assuming that each stock is traded once per month, each year will see 60 trades. In the “worst” case of FCNTX, which shows an average excess return to the hedged portfolio of 2.48 percent per month without transaction costs, the effective annual return is 34.17 percent. Roughly calculated, dividing this excess annual return by the 60 trades indicates the hedging portfolio still proves more appealing than the actual fund (in the second moment) if trades cost less than 0.57 percent on average.

Research on transaction cost indicates that large traders, such as in Fidelity's agreement with Lehman Brothers costs can be as low as approximately 2 to 2.5 cents per share.[21] This same book excerpt indicates an overall rate for sales traders, block traders, program traders, and algorithm trading for transaction costs are approximately 3.3 cents per share. According to another source, in fourth quarter 2004, NYSE (NASDAQ) transactions cost the average investment manager 0.26% (0.35%) per trade.[22] To remain conservative in our analysis, we assume the GA identifies only NASDAQ stocks and that each of the five stocks identified are traded every month. Thus we assume a monthly loss of approximately 1.75% due to transaction costs. Continuing the ACMVX example shown above, the circled points in Table 10, Panel B show the monthly effect in the return-risk space of monthly transactions costs of 1.75 percent. The return to the GA-generated portfolio, (A) ACMVX, decreases by 1.75 percent compared to the return shown in Panel A. Even though (A) ACMVX exhibits a negative mean monthly return, an investor with typical mean-variance preferences would still prefer this GA-generated portfolio to the ACMVX fund return-risk combination. Overall, Figure 9, Panel B demonstrates that even with this conservative assumption toward transaction costs, the GA hedging portfolios remain unambiguously better out-of-sample than the target funds in 9 of 10 cases for the calendar year 2008.

Besides the Sharpe Ratio, Columns 6 and 7 show the comparison of Jensen's alpha using a single factor (i.e., CAPM) model. In 6 of the 10 funds, the Jensen's alpha is absolutely higher for the GA-generated portfolio than for the target fund out-of-sample.

---

[21] http://www.automatedtrader.net/online-exclusive/631/transaction-cost-research

[22] http://www.capco.com/files/pdf/71/02_SERVICES/06_Market%20impact%20Transaction%20cost%20analysis%20and%20the%20financial%20markets%20%28Opinion%29.pdf

However, in only 2 of these cases (i.e., ACMVX and FBALX) is the alpha significantly different than zero. Our caveat with this measure is that we do not set up the fitness function to maximize this Jensen's alpha measure, so these results are but a positive externality of the fitness function we define in equation (7). Certainly altering the fitness function to incorporate alpha is a possibility when applying the GA technique, and we leave it for future research. Overall, it appears from this sample of mutual funds that using the GA allows one to mimic various mutual funds quite well and possibly outperform them out-of-sample in the first two statistical moments.

Finally, since mutual funds exhibit a short-selling constraint, we move to Exchange-Traded Funds, or ETFs, which do allow short positions. This time we use 5 randomly-selected ETFs as the target series for this GA technique. Table 8 and its Panels A through E, along with Figure 10 Panels A and B, depict the results for these ETFs that are analogous to the mutual fund results provided earlier. The ETFs sampled are EWC (April 1996 to December 2008), DIA (January 1998 to December 2008), IWD (May 2000 to December 2008), IXN (November 2001 to December 2008), and IJT (August 2000 to December 2008). As with the mutual funds results, the GA finds quite effective mimicking, or hedging, portfolios for these random ETFs. In every case the hedged portfolio of going long the five-asset portfolio and shorting the ETF reduces the out-of-sample variance relative to simply going short the ETF. This reduction ranges from approximately 17 (EWC) to 85 percent (IXN). Additionally, in every case shown there exists an average positive excess return to holding the hedged portfolio. This monthly (annual) return premium ranges from 1.74 (22.92) to 4.39 (67.51) percent in our out-of-sample period. The correlations are again positive in all ETF cases. The Sharpe ratios

for the hedging portfolios outpace those for the target ETFs in every case, and the Jensen's alpha measures are again mixed. Figure 10 Panel A (Panel B) shows the performance of the ETF and GA-generated hedging portfolio in mean/standard deviation space without (with) transaction costs as conservatively quantified earlier. In all five cases the GA set of assets is preferred, even when we include the assumed transaction costs as discussed with mutual funds. In summary, the GA again generates effective out-of-sample hedging portfolios.

To reiterate the caveat discussed earlier, while the results shown so far appear to support the GA as a viable technique to create hedging portfolios, we have started the Test Period in the case of each target, whether macroeconomic series, mutual fund, or ETF, to maximize the amount of time series information possible. There is certainly merit to using a shorter time horizon for estimating asset weights than beginning in 1967 since using data from four decades ago inherently assumes relationship stability that has existed over that timeframe will continue for another 12 months. It is almost a certainty that using a shorter Test Period will change the results, but we cannot currently speculate as to the direction. Therefore, we leave this data collection and incorporation effort to a future generation of this research.

Conclusions

Historically it seems the effort to tie asset pricing theory and empirical phenomena has focused on using macroeconomic data to explain asset returns (e.g., Chen, Roll, and Ross (1986)). However, there exist important risk-reduction reasons for using investable assets to "explain" or more appropriately, hedge, non-investable

macroeconomic series. In just one example, as Jennings, Fraser, and Payne (2009) highlight, many large entities could benefit from reducing their future exposure to medical care costs. From an insurance standpoint, there exist an almost boundless number of non-investable risky phenomena that one might wish to protect against by investing in particular assets. For example, property insurers might wish to manage the risk imposed by construction costs, or mass carriers might wish to offset their transportation or energy consumption risk. The Genetic Algorithm (GA) technique presented in this paper provides a viable alternative for addressing such problems.

The purpose of this paper is to demonstrate that the Holland (1975) Genetic Algorithm (GA) process can find such hedging portfolios based on user-defined parameters in a relatively efficient manner. In the case of medical inflation, across the out-of-sample time period from 2005 to 2008, these five-asset GA-generated portfolios appear to perform much better than the current investable mutual funds at managing the risk of escalating health care expenses. Using these GA-generated hedging portfolios at worst approximates the same risk (i.e., variance) level as exposure to medical inflation itself, but they also provide superior returns in the out-of-sample months investigated, resulting in an entity's ability to fully fund the associated liabilities by investing in these portfolios.

The results for nine other macroeconomic series presented here, while mixed overall, generally show a weakly-preferred situation. The GA-generated portfolios at least provide an opportunity for entities to tradeoff their desired levels of risk and return. It is rare that the hedged position formed by holding a long position in the GA portfolio against a natural short position in the macroeconomic series presents an unambiguously

worse scenario for the hedging entity. In only 4 of the 40 series-year combinations (PPI residential construction in 2008, transportation inflation in 2007, diesel fuel in 2006, and Case-Shiller 10-City Composite Index in 2005) are the hedged portfolio variance higher than the target series and the entity underfunded in the out-of-sample year. On the other hand, for almost three times as many (11) of the series-year combinations, the GA-recommended hedged position unambiguously improves a hedging entities situation by fully funding the liability with less out-of-sample risk. The remaining 25 series-year combinations allow the liable party to tradeoff risk and return when deciding whether to manage its risk using the GA portfolio.

The GA technique described in this paper provides a mechanism to find commonly-traded asset combinations to address exposure to non-traded risk. One extension of this research could involve including additional assets in the hedging portfolios (e.g., 10 stocks) with the hope of decreasing the inherent unsystematic risk in the existing portfolios. And the results for tracking investable assets, while less robust in this presentation, are encouraging and present another avenue for future research.

References

Bauer, Richard J., 1994, Genetic Algorithms and Investment Strategies (John Wiley & Sons, NY).

Bodie, Zvi, 1976, Common stocks as a hedge against inflation, *Journal of Finance* 31, 459-470.

Brandt, Michael W., and Pedro Santa-Clara, 2006, Dynamic portfolio selection by augmenting the asset space, *Journal of Finance* 61, 2187-2218.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Cochrane, John H., 1996, A cross sectional test of an investment based asset pricing model, *Journal of Political Economy* 104, 572-621.

De Jong, K., 1975, An analysis of the behavior of a class of genetic adaptive systems, PhD dissertation, University of Michigan.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Flannery, Mark J. and Aris A. Protopapadakis, 2002, Macroeconomic factors do influence aggregate stock returns, *Review of Financial Studies* 15, 751-82.

Holland, John H., 1975, Adaptation in Natural and Artificial Systems (University of Michigan, MI).

Jennings, William W., Steven Fraser, and Brian C. Payne, 2009, Do health care investments hedge health care liabilities? *Journal of Investing* 18, 69-74.

Jensen, Michael C., 1968, The performance of mutual funds in the period 1945-1964, *Journal of Finance* 23, 389-416.

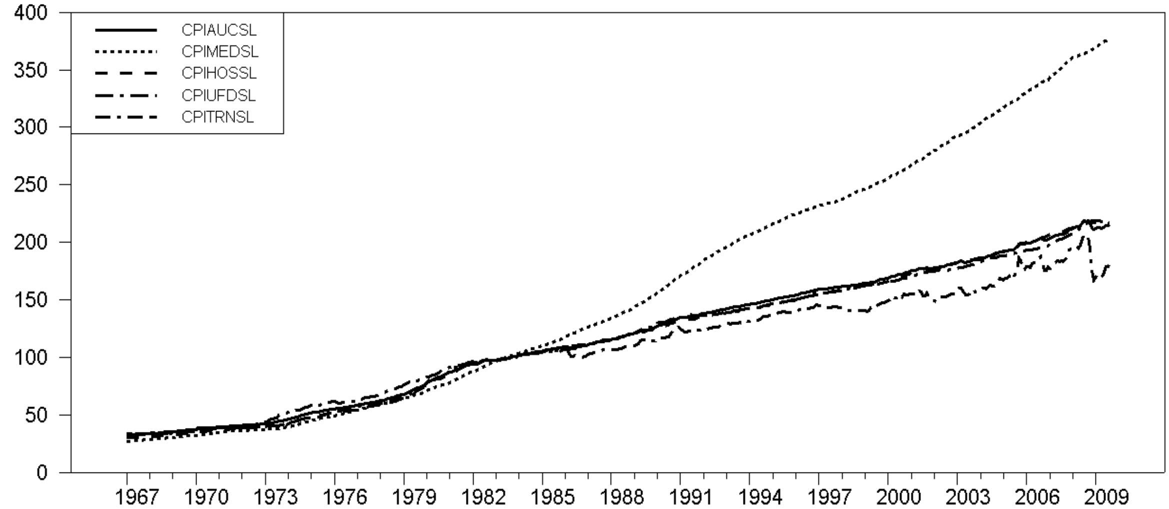
Lamont, Owen, 2001, Economic tracking portfolios, *Journal of Econometrics* 105, 161-84.

Sharpe, William F., 1966, Mutual fund performance, *Journal of Business* 39, 119-38.

Statman, Meir, 1987, How many stocks make a diversified portfolio? *Journal of Financial and Quantitative Analysis* 22, 353-63.

Appendix A
Figures

Figure 1
Monthly Consumer Price Index (CPI) Measures
January 1967-August 2009



CPIAUCSL: Aggregate CPI
CPIMEDSL: Medical Component of CPI
CPIHOSSL: Housing Component of CPI
CPIUFDSL: Food Component of CPI
CPITRNSL: Transportation Component of CPI

Figure 2
Initial Population for Genetic Algorithm (GA)

	Assets included in the Candidate Solution					
Candidate Solution #	**Ret(i)**	**Ret(j)**	**Ret(k)**	**Ret(l)**	**Ret(m)**	**Fitness Level**
1	1	7	25	36	41	1.02
2	23	9	7	29	31	0.8
3	7	3	2	19	15	2
*	*	*	*	*	*	*
*	*	*	*	*	*	*
*	*	*	*	*	*	*
721	22	15	14	9	38	1.05
*	*	*	*	*	*	*
*	*	*	*	*	*	*
1000	2	6	28	7	11	0.25

We choose 1,000 possible asset combinations to form hedge portfolios. These are referred to as parents or candidate solutions. Each candidate solution includes the return series from 5 assets out of a universe of 3,000 assets. For example, candidate 1 forms a hedge portfolio using assets 1,7, 25, 36, and 41. The hedge is estimated by equally-weighting these assets into a portfolio according to the equation below,

$$Ret_{Hedge,t} = 0.2 * Ret(i)_t + 0.2 * Ret(j)_t + 0.2 * Ret(k)_t + 0.2 * Ret(l)_t + 0.2 * Ret(m)_t$$

where i = 1, j = 7, k = 25, l = 36, and m = 41.

The degree of hedging effectiveness is then calculated and recorded as the candidate's fitness level. Fitness levels indicate the extent to which the objective function (see equation (1)) is optimized.

Figure 3
GA Pairing Example

Panel A
Ranking by Fitness

Candidate Solution #	Ret(i)	Ret(j)	Ret(k)	Ret(l)	Ret(m)	Fitness Level
1000	2	6	28	7	11	0.25
2	23	9	7	29	31	0.8
1	1	7	25	36	41	1.02
721	22	15	14	9	38	1.05
3	7	3	2	19	15	2
*	*	*	*	*	*	*

The initial candidate population is ranked according to fitness. The most fit candidates are called the breeding population.

Panel B
Pairing 1: Crossover Equal to 2

Candidate Solution #	Ret(i)	Ret(j)	Ret(k)	Ret(l)	Ret(m)	Fitness Level
1000	2	6	28	7	11	0.25
2	23	9	7	29	31	0.8
Offspring 1	23	9	28	7	11	
Offspring 2	2	6	7	29	31	

Candidate 1000 and 2 constitute the first pairing based on their best fitness. They produce two offspring or alternative solutions by the process of crossover. With a crossover of 2, Ret(i) and Ret(j) from candidate 1000 and 2 are swapped while the remaining three assets remain the same.

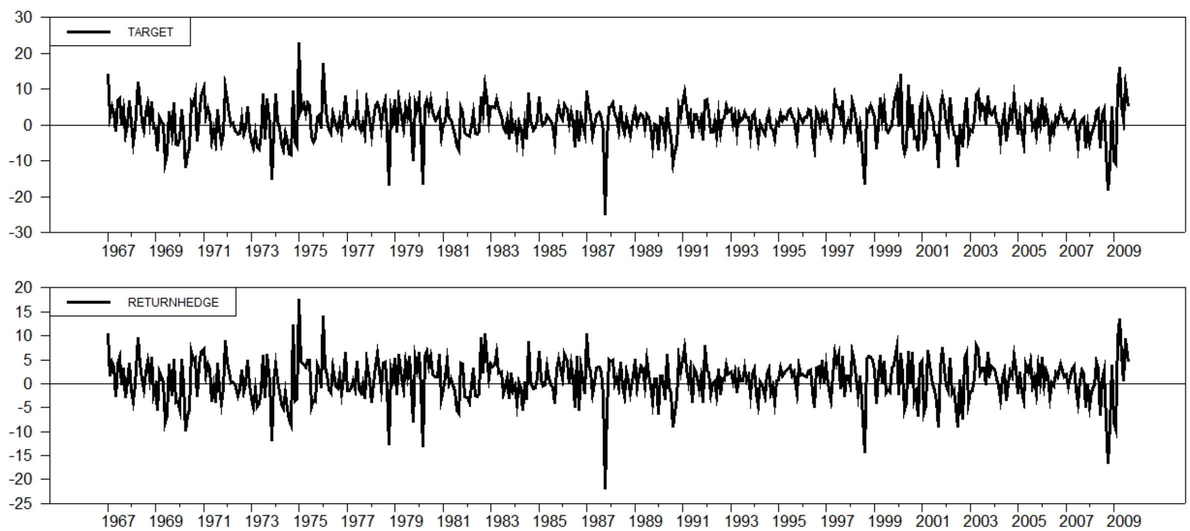
Panel C
Pairing 2: Crossover Equal to 3

Candidate Solution #	Ret(i)	Ret(j)	Ret(k)	Ret(l)	Ret(m)	Fitness Level
1	1	7	25	36	41	1.02
721	22	15	14	9	38	1.05
Offspring 3	22	15	14	36	41	
Offspring 4	1	7	25	9	38	

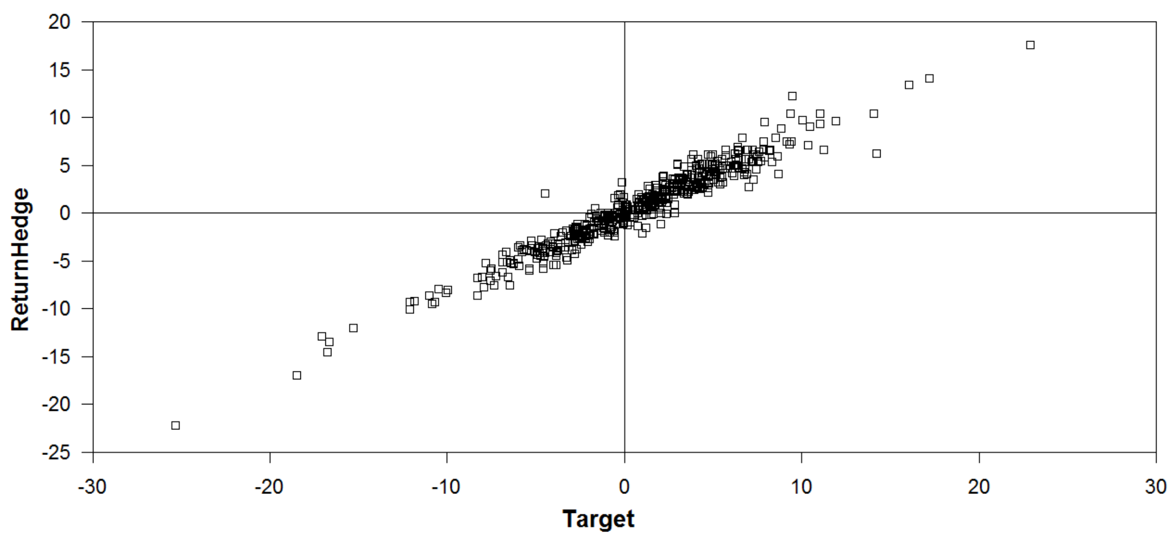
Candidate 1 and 721 constitute the second pairing based on their fitness. They produce two offspring or alternative solutions by the process of crossover. With a crossover of 3, Ret(i) , Ret(j) and Ret(k) from candidate 1 and 721 are swapped while the remaining two assets remain the same.

Figure 4
GA Proof of Concept Performance

Panel A
Monthly Return of Target Series ("Target") versus Best Hedging Portfolio ("Returnhedge") Chosen by the GA
January 1967-August 2009



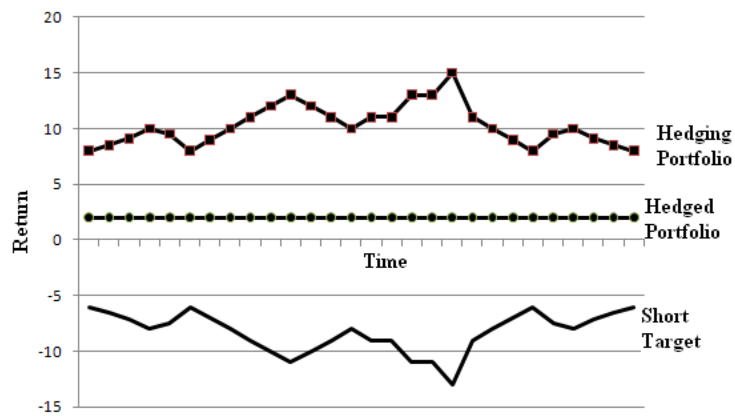
Panel B
Scatter Plot of Target Series ("Target") versus Hedging Portfolio ("Returnhedge")
January 1967-August 2009



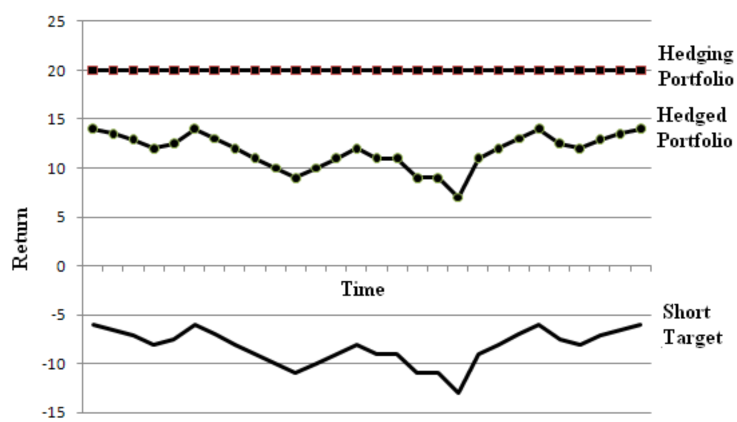
Correlation = 0.96

Figure 5
Hedging Portfolio Examples

Panel A: Ideal Hedging Portfolio



Panel B: Uncorrelated (Constant Return) Hedging Portfolio Example



Panel B: Correlated (Varying Return) Hedging Portfolio Example

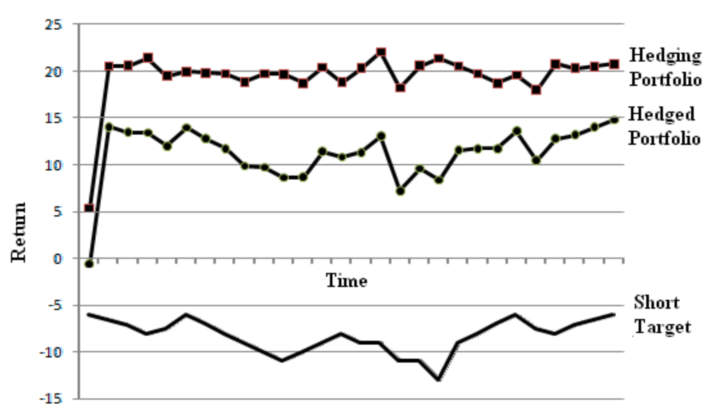
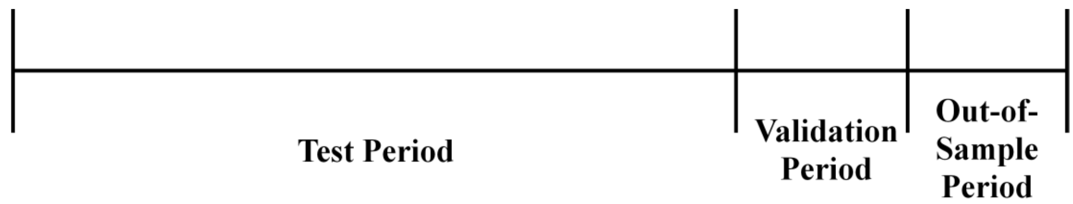


Figure 6
Division of the Data and Evaluation of Fitness



The “Test” period (January 1967-December 2006) is used to estimate the hedge ratio parameters for $\hat{a}_0 \ldots . \hat{a}_5$ and $\hat{b}_0 \ldots . \hat{b}_5$ using OLS regression. The hedging effectiveness is measured over both the “Testing” period and the “Validation” period (January 2007-December 2007). Note that “Validation” period is outside the range used to estimate the parameters. The “Out-of-Sample” period is the 12 months spanning January 2008-December 2008. The variance of H_t for the “Test” and “Validation” periods is used to measure the extent to which the hedge candidate optimizes the objective function (called the fitness). We define as our “fitness” a weighted average of the two variance measures:

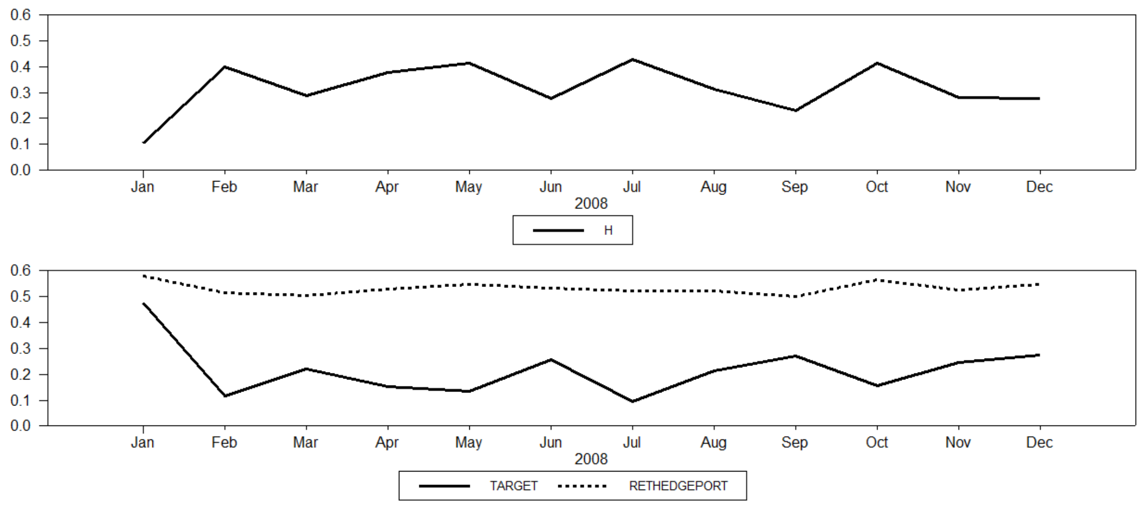
$$Fitness = w_1 \sigma^2_{H,Test} + w_2 \left(\frac{\sigma^2_{H,Validation}}{\sigma^2_{H,Test}} \right)$$

$\sigma^2_{x,y}$ is the variance of series x during period y. x consists of the hedging portfolio consisting of five assets, the target series (i.e., medical inflation in this case), or the hedged portfolio, *H*, which represents a long position in the hedging portfolio and short position in the target series (i.e., medical inflation). y consists of the Test, Validation, or Out-of-Sample period as shown and described above. (w_1, w_2) represent the subjectively-assigned weights for each respective term.

Figure 7
Genetic Algorithm Portfolio Performance for Out-of-Sample Period
January 2008-December 2008

Panel A: Weight Vector (1,1)

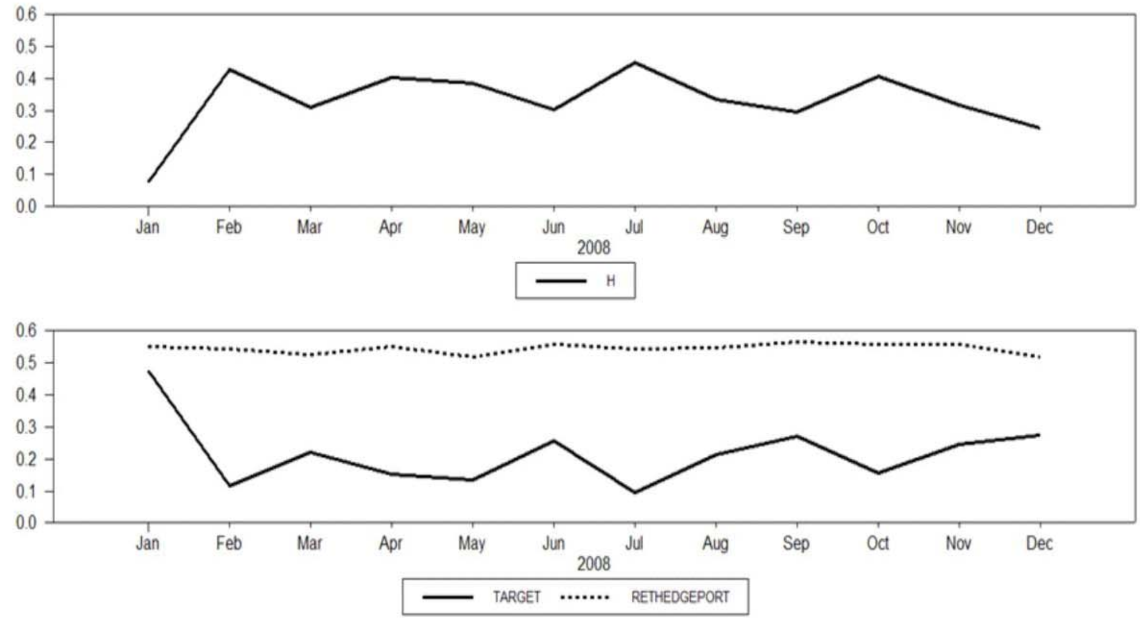
Monthly Returns for Hedged Portfolio (H), Genetic Algorithm Hedging Portfolio (RETHEDGEPORT), and Medical Inflation (TARGET) for Out-of-Sample Period



GA Hedging Portfolio Assets and Weights

Stock Number	Industry Membership	Relative Weight
274	Processed & Packaged Goods	-1.12
79	Entertainment	-0.38
199	Specialty Retail	0.39
33	Security & Protection Services	-0.11
214	Industrial Equipment	0.21

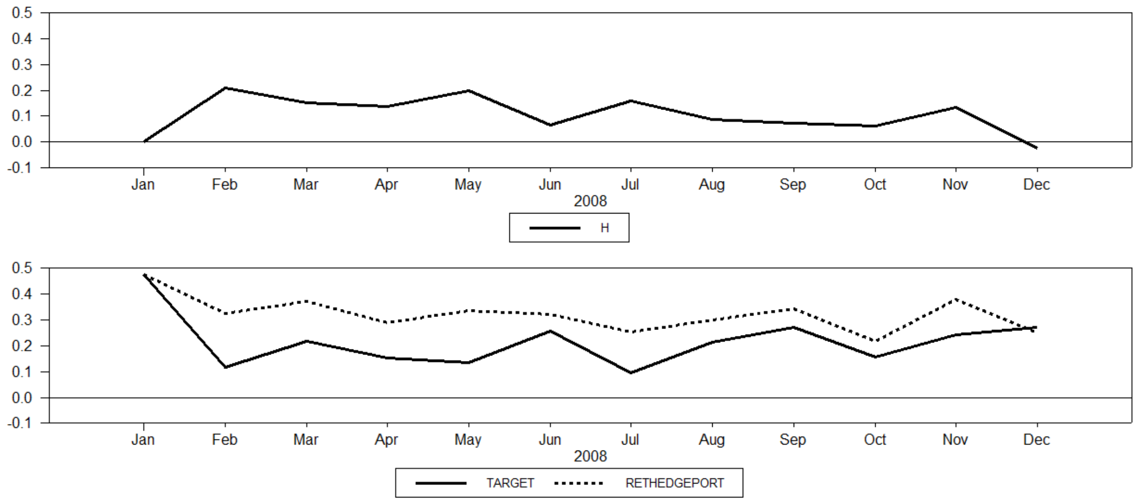
Panel B: Weight Vector (0,1)



GA Hedging Portfolio Assets and Weights

Stock Number	Industry Membership	Relative Weight
81	Chemicals	-0.11
76	Business Equipment	-0.02
84	Electric Utilities	-0.53
229	Manufacturing	0.02
117	Steel & Iron	-0.36

Panel C: Weight Vector (1,0)

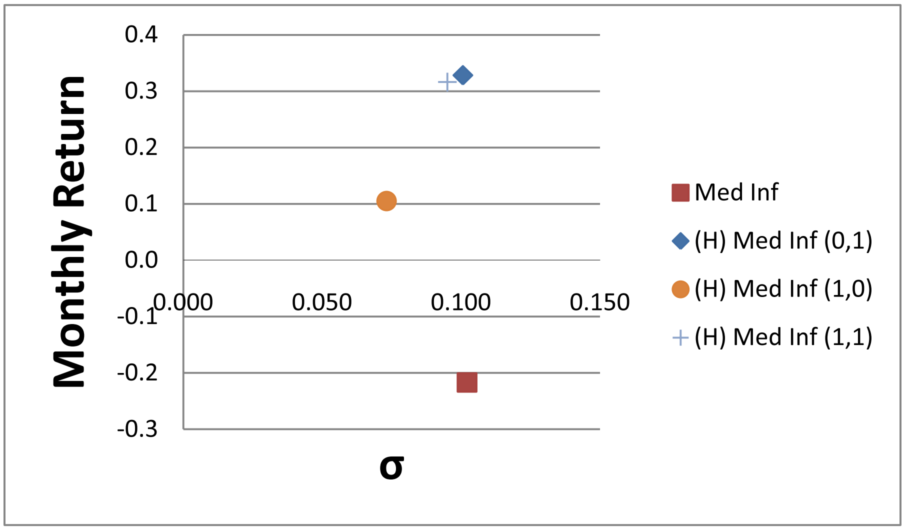


GA Hedging Portfolio Assets and Weights

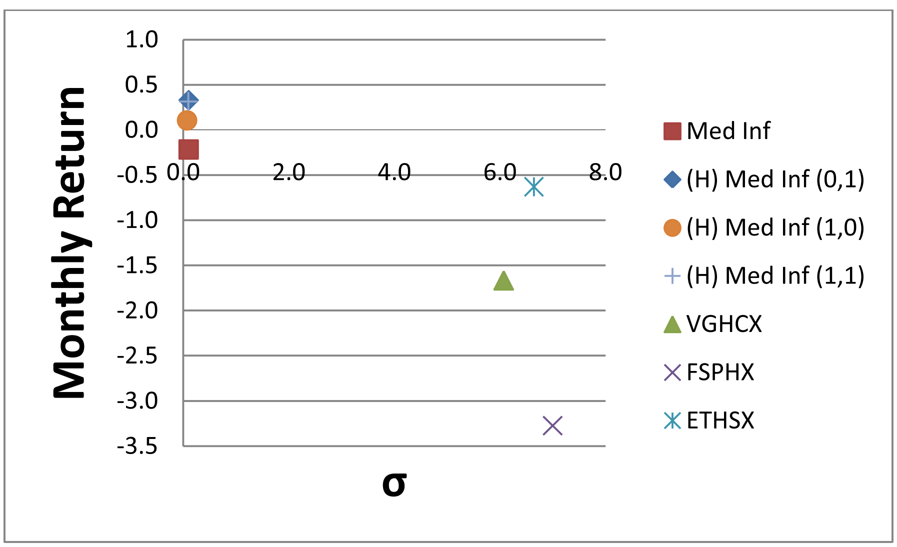
Stock Number	Industry Membership	Relative Weight
306	T-Bill	1.00
297	Accident & Health Insurance	0.00
288	Restaurants	0.00
225	Rental & Leasing Services	0.00
32	Telecommunications	0.00

Figure 8
Medical Inflation and Potential Hedging Portfolio Return Characteristics in Mean-Standard Deviation Space for Out-of-Sample Period
January 2008-December 2008

Panel A: GA Portfolios Relative to Each Other



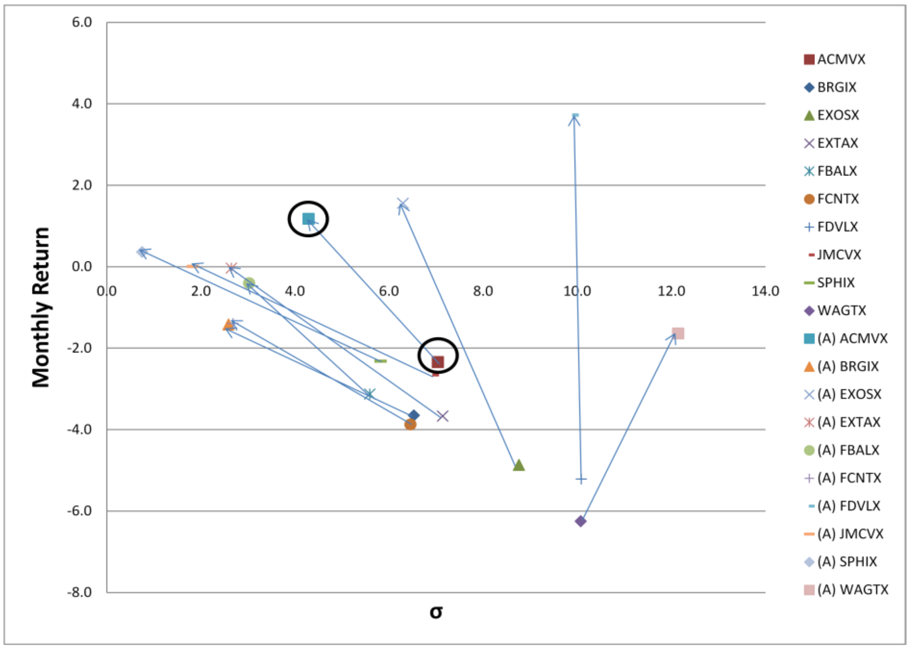
Panel B: GA Portfolios Relative to Other Health-Care Related Mutual Funds



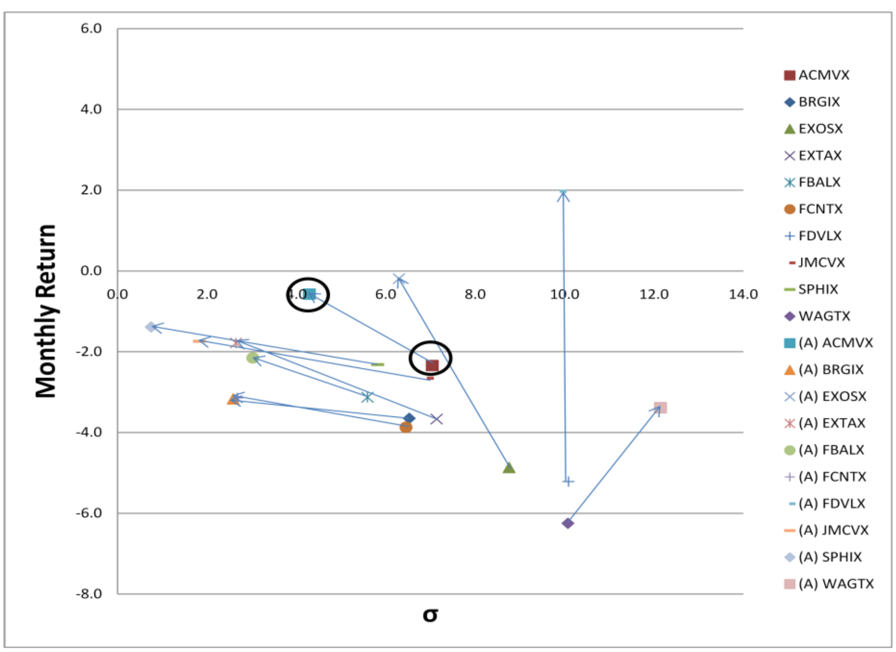
Definitions:
Med Inf: medical inflation series
(H) Med Inf (x,y): hedged portfolio ($Ret_{Portfolio}$ – Medical Inflation) using $(w_1,w_2) = (x,y)$
ETHSX: Eaton Vance Worldwide Health Science A
VGHCX: Vanguard Health Care
FSPHX: Fidelity Select Health Care

Figure 9
Mutual Fund and Potential Hedging Portfolio Return Characteristics
Mean-Standard Deviation Space
Out-of-Sample Period
January 2008-December 2008

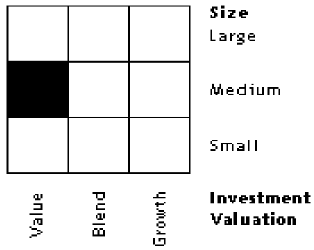
Panel A: No Transaction Costs



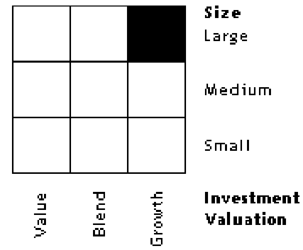
Panel B: 1.75% per month Transaction Costs



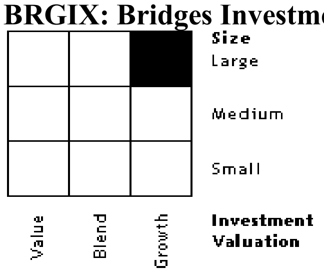
ACMVX: American Century Mid Cap Value Inv



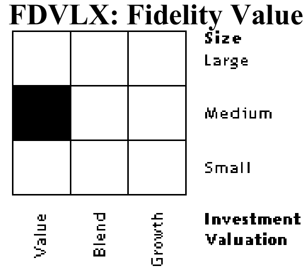
FCNTX: Fidelity Contrafund



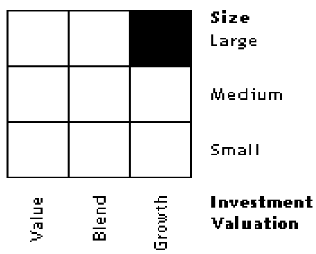
BRGIX: Bridges Investment



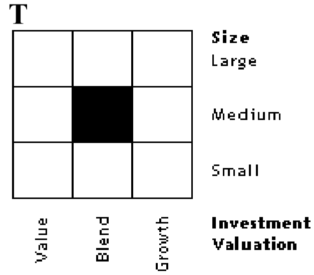
FDVLX: Fidelity Value



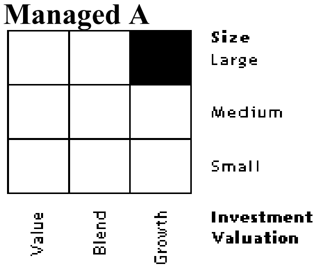
EXOSX: Manning & Napier Overseas



JMCVX: Janus Perkins Mid Cap Value T



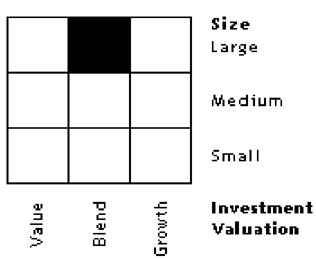
EXTAX: Manning & Napier Tax Managed A



SPHIX: Fidelity High Income

Unavailable

FBALX: Fidelity Balanced



WAGTX: Wasatch Global Science & Technology

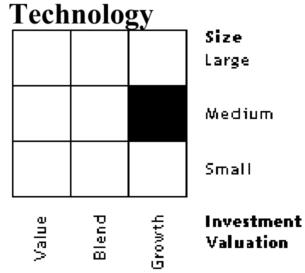
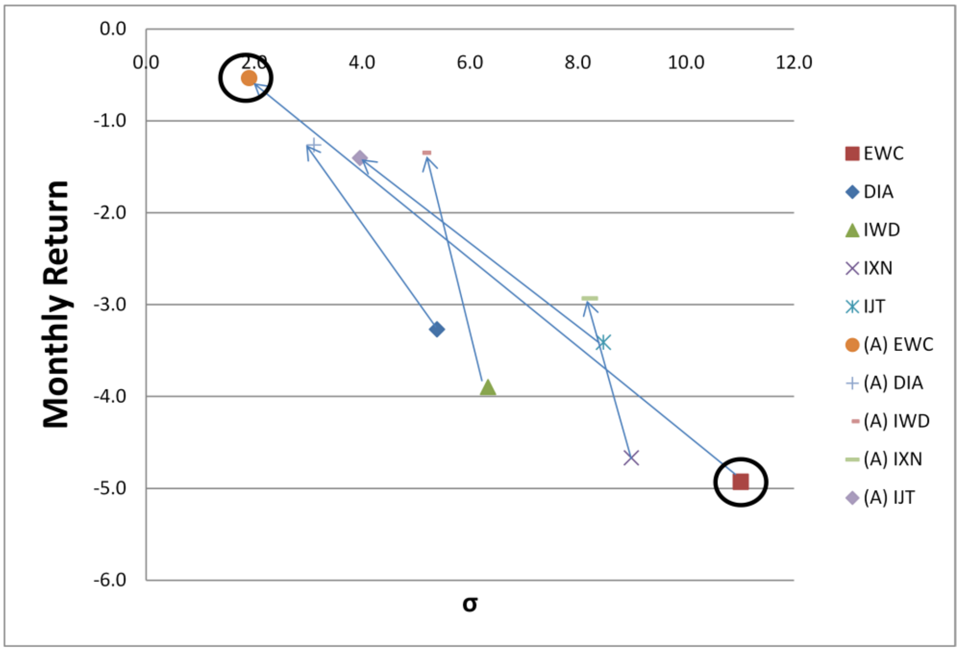
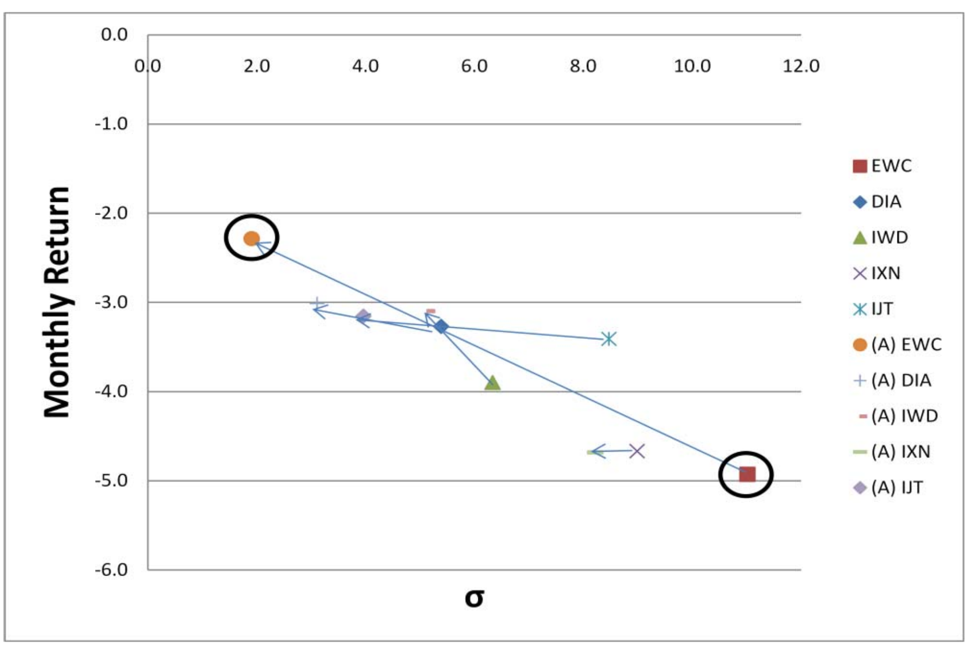


Figure 10
Exchange-Traded Fund (ETF) and Potential Hedging Portfolio Return Characteristics
Mean-Standard Deviation Space
Out-of-Sample Period
January 2008-December 2008

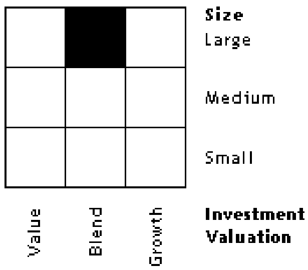
Panel A: No Transaction Costs



Panel B: 1.75% per month Transaction Costs



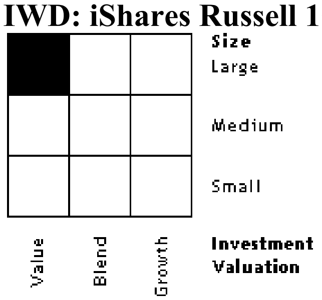
EWC: iShares MSCI Canada Index



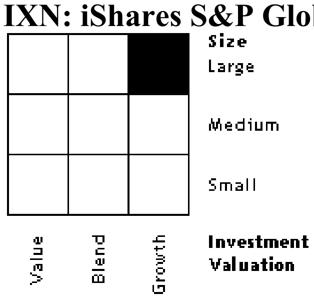
DIA: SPDR Dow Jones Industrial Average

Unavailable

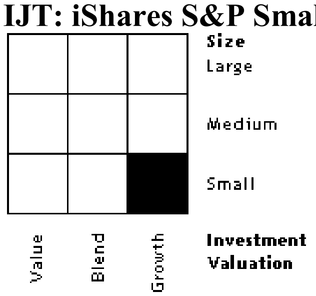
IWD: iShares Russell 1000 Value Index



IXN: iShares S&P Global Technology



IJT: iShares S&P SmallCap 600 Growth



Appendix B
Tables

Table 1
Fitness Level for Asset Portfolios across Generations using Proof of Concept Returns
January 1967-August 2009

	Population			Breeding Sample
Generation	Minimum Fitness Level	Mean Fitness Level	Maximum Fitness Level	Mean Fitness Level
1	7.61	40.34	309.31	21.12
2	7.00	36.09	379.93	13.43
3	5.29	37.36	302.12	9.30
4	4.68	38.27	358.80	7.44
5	4.28	36.60	480.70	5.83
6	4.28	37.98	423.33	4.86
7	4.28	41.47	234.77	4.46
8	4.28	56.43	359.41	4.28
9	4.28	54.81	338.54	4.28
10	4.28	56.56	349.44	4.28

This table shows how the GA population evolves over many generations. Fitness level is the quantified measure for the variance of a time series called $Error$, which is the difference between a target series and portfolio of five assets seeking to hedge the target series. The objective function is shown below.

$$Minimize\ Variance(Error)$$
$$\text{where } Error_t = Ret_{Hedge\ Portfolio\ ,t} - Ret_{Target\ ,t}$$

$Ret_{Target\ ,t}$ ($Ret_{Hedge\ Portfolio\ ,t}$) is the return of the target series (hedge portfolio series) at time t.

In this proof of concept example, the hedging assets are simulated investable assets, with representative factor loadings. To generate the simulated assets, we estimate betas of a five-factor model for each asset from a random sample of 3,000 assets from CRSP, pulled from the 16,000+ assets with at least 60 months' returns between January 1967 and December 2008. The five factors include the market risk premium, SMB, HML, default risk premium (DEF), and term risk premium (TERM). The target series is a simulated asset composed of the median factor beta values from the 3,000 sampled assets.

In the table, minimum fitness level is for the portfolio of five assets among the entire breeding population, which has 1,000 members, that has the lowest, or best, fitness measure. The mean (maximum) fitness level is the population mean (maximum). In this example, the breeding population consists of 10 percent of the population, or 100 members, and the final column shows the mean fitness level for this breeding sub-population.

Table 2
Fitness Level for Asset Portfolios over Generations using Actual Target (Medical Inflation) and Investable Assets (303 Stocks from CRSP, Long Government Bond, Short Government Bond, and Treasury Bill) During the Test and Validation Periods
January 1967-December 2007

Weight = (1,1)	Population			Breeding Sample
Generation	Minimum Fitness Level	Mean Fitness Level	Maximum Fitness Level	Mean Fitness Level
1	0.271	0.339	0.504	0.301
2	0.250	0.338	0.504	0.282
3	0.246	0.332	0.536	0.268
4	0.242	0.333	0.506	0.258
5	0.242	0.339	0.575	0.254
6	0.240	0.343	0.609	0.251
7	0.233	0.339	0.533	0.248
8	0.233	0.339	0.521	0.245
9	0.233	0.337	0.500	0.242
10	0.233	0.347	0.516	0.242

This table shows how the GA population evolves over many generations. Fitness level is the quantified by the following.

$$Fitness = w_1 \sigma^2_{H,Test} + w_2 \left(\frac{\sigma^2_{H,Validation}}{\sigma^2_{H,Test}} \right)$$

$\sigma^2_{x,y}$ is the variance (mean) of series x during period y. x consists of the hedging portfolio consisting of five assets, the target series (i.e., medical inflation in this case), or the hedged portfolio, *H,* which represents a long position in the hedging portfolio and short position in the target series (i.e., medical inflation). y consists of the Test, Validation, or Out-of-Sample period as shown and described above. (w_1, w_2) represent the subjectively-assigned weights for each respective term and equal to (1,1) here.

The investable assets in this example consist of 303 stocks from CRSP that have returns from January 1967 to December 2008 and three government bond/bill return series (i.e., 10-year bond, one-year bond, and 30-day bill).

In the table, minimum fitness level is for the portfolio of five assets among the entire breeding population, which has 1,000 members, that has the lowest, or best, fitness measure. The mean (maximum) fitness level is the population mean (maximum). In this example, the breeding population consists of 10 percent of the population, or 100 members, and the final column shows the mean fitness level for this breeding sub-population.

Table 3
Portfolio Hedging Effectiveness against Medical Inflation
Out-of-Sample Period
January 2008-December 2008

Weights (w_1, w_2)	**Variance Ratio** $\left(\frac{\sigma^2_{H,OutofSample}}{\sigma^2_{Target,OutofSample}}\right)$	**Assets (Return Series Stock Number)**					**Generation Converged**	**Mean Excess Monthly Return of Hedging Portfolio vs. Medical Inflation**
(1,1)	0.866	274	79	199	33	214	9	0.316
(0,1)	0.971	81	76	84	229	117	7	0.328
(1,0)	0.513	306	297	288	225	32	3	0.105

Column 1 shows the weights implemented in the fitness measure shown in equation (7). Column 2 depicts the ratio of the variance of the hedged portfolio, *H*, to the variance of medical inflation for the Out-of-Sample period (January 2008-December 2008). Column 3 shows the assets that compose the hedging portfolio. Each number, 1 to 306, represents an index referring to a return series of an traded stock or government bond who has returns in CRSP from January 1967 to December 2008. "Generation Converged" shows the generation of the genetic algorithm where the best solution appears to have stabilized. The final Column quantifies the mean monthly excess return to the hedging portfolio over the mean monthly medical inflation, or Ret(Hedge) – CPIMEDMO, for the Out-of-Sample period.

Assets	
Stock Number	**Industry Membership**
274	Processed & Packaged Goods
79	Entertainment
199	Specialty Retail
33	Security & Protection Services
214	Industrial Equipment
81	Chemicals
76	Business Equipment
84	Electric Utilities
229	Manufacturing
117	Steel & Iron
306	T-Bill
297	Accident & Health Insurance
288	Restaurants
225	Rental & Leasing Services
32	Telecommunications

Table 4
Hedging Portfolio Performance in Funding $1M Health Care Liability
January 2008-December 2008

	Medical Inflation (%)	Health Care Costs ($M)	Portfolio Return (%)	Portfolio Assets ($M)	Initial Investment Required to Offset Cost ($M)	Excess at Time 0 (%)
Jan	0.48	1.005	0.57	1.006	0.999	0.09
Feb	0.12	1.006	0.53	1.011	0.995	0.50
Mar	0.22	1.008	0.53	1.016	0.992	0.81
Apr	0.15	1.010	0.53	1.022	0.988	1.19
May	0.14	1.011	0.45	1.026	0.985	1.50
Jun	0.26	1.014	0.56	1.032	0.982	1.80
Jul	0.10	1.015	0.54	1.038	0.978	2.23
Aug	0.21	1.017	0.51	1.043	0.975	2.51
Sep	0.27	1.019	0.60	1.049	0.972	2.84
Oct	0.15	1.021	0.66	1.056	0.967	3.32
Nov	0.24	1.024	0.57	1.062	0.964	3.64
Dec	0.27	1.026	0.58	1.068	0.961	3.93

This table presents the funding performance of an investment in the medical inflation hedging portfolio consisting of assets 81, 76, 84, 229, and 117. Assuming an entity is setting aside $1 million to fund the anticipated medical care expense it will incur sometime during 2008, Column 2 shows monthly medical inflation, with Column 3 showing what the $1 million liability would cost if incurred at the end of the associated month. Column 4 shows the monthly hedging portfolio return, and Column 5 translates these returns into dollar values if the $1 million set-aside is invested in the hedging portfolio. Column 6 shows how much of the original $1 million would have been needed to offset the liability exactly, with Column 7 showing the excess initial funds as a percentage at the beginning of the year if the whole liability were to occur at the end of the associated month.

Table 5
Hedge Ratios for "Good" Genetic Algorithm Portfolio for Test Period
January 1967-December 2006

	Parameter	P-Value
Constant	0.537	0.000
Ret(81)	-0.00037	0.850
Ret(76)	-0.00006	0.970
Ret(84)	-0.00171	0.453
Ret(229)	0.00007	0.938
Ret(117)	-0.00118	0.556
R-Squared	0.003	
N	420	

OLS regression results for the following specification,

$$CPIMEDMO_t = a_0 + a_1 Ret(81) + a_2 Ret(76) + a_3 Ret(84) + a_4 Ret(229) + a_5 Ret(117)$$

for the Test Period, January 1967 to December 2006, where is monthly medical inflation and is the return series for a stock bond with index x. The estimated parameters represent the hedge ratios for each respective asset x. The weight vector (w_1, w_2) equals (0,1) for the fitness function (see equation (6)) used to generate this hedging portfolio.

Assets	
Stock Number	**Industry Membership**
81	Chemicals
76	Business Equipment
84	Electric Utilities
229	Manufacturing
117	Steel & Iron

Table 6
MACROECONOMIC SERIES

Monthly Out-of-Sample Results for Macroeconomic Series of Interest Using Annually-Established Policy Rule

Panel A
Validation Period: January-December 2007
Out-of-Sample Period: January-December 2008
Test Period: Varies-December 2006

Macroeconomic (Target) Series	$\frac{\sigma_H^2}{\sigma_{Target}^2}$	$\bar{H}$ (Monthly)	$\bar{H}$ (Annual)	$\rho_{Target,Portfolio}$	Assets					Series Beg - End (Mo/Yr)
					1	2	3	4	5	
Medical Inflation	0.97	0.33	4.01	0.17	81	76	84	229	117	1/67 - 12/08
Housing Inflation	1.01	0.24	2.95	0.10	84	90	192	145	82	1/67 - 12/08
Case-Shiller 10-City Composite	1.29	2.46	33.80	-0.19	194	46	192	108	156	1/67 - 12/08
PPI Residential Construction	1.16	-0.01	-0.12	-0.46	26	188	291	87	192	6/86 - 12/08
Energy Inflation	1.01	0.24	2.95	0.10	84	90	192	145	82	1/67 - 12/08
Transportation Inflation	1.01	1.76	23.23	0.01	288	229	192	149	49	1/67 - 12/08
Oil Spot Price*	1.02	7.40	135.56	-0.19	51	137	185	231	287	1/67 - 12/08
Jet Fuel Spot Price	1.13	6.54	113.92	-0.38	263	184	174	172	219	4/90 - 12/08
Diesel Fuel PPG	1.01	3.79	56.28	0.03	204	199	37	45	229	3/94 - 12/08
Aggregate Inflation	0.99	0.41	5.05	0.15	253	16	198	266	192	1/67 - 12/08
S&P 500	0.62	3.38	49.10	0.70	41	44	11	20	189	1/67 - 12/08
Notes:										
Weights (0,1)										
*Best solution in 10th generation; convergence not guaranteed										

This table summarizes the hedging performance for a portfolio of five assets identified by the Genetic Algorithm (GA) technique using the fitness function in equation (6) for the out-of-sample period December to January 2008. Column 1 shows the target macroeconomic series. Column 2 shows the variance ratio of the hedged portfolio, *H*, which consists of a long position in the five-asset hedging portfolio and a short position in the target macroeconomic series. Column 3 (4) shows the average monthly (annualized) return of the hedged portfolio, *H*. Column 5 shows the Pearson correlation between the target macroeconomic series and the five-asset hedging portfolio. Columns 6-10 identify the investable assets that from the portfolio by their author-generated index numbers. Please see Appendix C for a list of the industries associated with these assets. The final column shows the relevant time period for the target macroeconomic series. Future Panels show the same results for Out-of-Sample periods 2007, 2006, and 2005.

Table 6
Panel B
Validation Period: January-December 2006
Out-of-Sample Period: January-December 2007
Test Period: Varies-December 2005

Macroeconomic (Target) Series	$\frac{\sigma_H^2}{\sigma_{Target}^2}$	$\bar{H}$ (Monthly)	$\bar{H}$ (Annual)	$\rho_{Target,Portfolio}$	Assets					Series Beg - End (Mo/Yr)
					1	2	3	4	5	
Medical Inflation	0.90	0.13	1.58	0.34	229	87	13	272	251	1/67 - 12/07
Housing Inflation*	1.03	0.16	1.99	-0.03	196	192	247	21	30	1/67 - 12/07
Case-Shiller 10-City Composite*	1.04	1.43	18.53	-0.54	254	186	53	215	190	1/67 - 12/07
PPI Residential Construction	0.99	-0.42	-4.96	0.21	192	153	138	175	56	6/86 - 12/07
Energy Inflation	0.94	-0.99	-11.27	0.24	146	288	51	192	15	1/67 - 12/07
Transportation Inflation	1.01	-0.25	-3.02	0.08	288	229	195	192	15	1/67 - 12/07
Oil Spot Price*	0.99	-2.50	-26.16	0.11	233	254	266	149	51	1/67 - 12/07
Jet Fuel Spot Price	0.86	-1.72	-18.81	0.37	72	203	3	229	25	4/90 - 12/07
Diesel Fuel PPG	0.98	-1.48	-16.34	0.16	10	229	89	287	105	3/94 - 12/07
Aggregate Inflation	1.02	0.10	1.16	0.09	229	287	200	192	15	1/67 - 12/07
S&P 500	0.87	0.37	4.59	0.38	125	84	219	249	117	1/67 - 12/07
Notes:										
Weights (0,1)										
*Best solution in 10th generation; convergence not guaranteed										

Table 6
Panel C
Validation Period: January-December 2005
Out-of-Sample Period: January-December 2006
Test Period: Varies-December 2004

Macroeconomic (Target) Series	$\frac{\sigma_H^2}{\sigma_{Target}^2}$	$\overline{H}$ (Monthly)	$\overline{H}$ (Annual)	$\rho_{Target,Portfolio}$	Assets					Series Beg - End (Mo/Yr)
					1	2	3	4	5	
Medical Inflation	1.07	0.24	2.95	-0.22	229	137	161	192	263	1/67 - 12/06
Housing Inflation	1.13	0.15	1.83	-0.53	216	132	229	243	194	1/67 - 12/06
Case-Shiller 10-City Composite*	0.88	0.53	6.60	0.35	187	289	138	40	275	1/67 - 12/06
PPI Residential Construction*	0.98	-0.28	-3.28	0.25	113	227	3	192	171	6/86 - 12/06
Energy Inflation	1.04	0.24	2.93	-0.04	304	288	51	229	237	1/67 - 12/06
Transportation Inflation	0.93	0.20	2.47	0.58	288	229	287	192	15	1/67 - 12/06
Oil Spot Price*	0.96	0.15	1.76	0.28	72	111	51	253	230	1/67 - 12/06
Jet Fuel Spot Price	1.01	0.74	9.26	0.05	229	70	66	114	198	4/90 - 12/06
Diesel Fuel PPG	1.13	-0.30	-3.57	-0.34	229	137	161	192	263	3/94 - 12/06
Aggregate Inflation	1.03	0.18	2.21	0.02	192	287	246	24	229	1/67 - 12/06
S&P 500	0.86	-0.84	-9.58	0.47	122	83	124	219	266	1/67 - 12/06
Notes:										
Weights (0,1)										
*Best solution in 10th generation; convergence not guaranteed										

Table 6
Panel D
Validation Period: January-December 2004
Out-of-Sample Period: January-December 2005
Test Period: Varies-December 2003

Macroeconomic (Target) Series	$\frac{\sigma_H^2}{\sigma_{Target}^2}$	$\bar{H}$ (Monthly)	$\bar{H}$ (Annual)	$\rho_{Target,Portfolio}$	Assets 1	Assets 2	Assets 3	Assets 4	Assets 5	Series Beg - End (Mo/Yr)
Medical Inflation	1.02	0.20	2.39	-0.13	157	199	229	253	277	1/67 - 12/05
Housing Inflation	0.99	0.10	1.22	0.09	197	86	192	46	257	1/67 - 12/05
Case-Shiller 10-City Composite	1.00	-0.77	-8.83	-0.02	287	15	249	46	48	1/67 - 12/05
PPI Residential Construction	0.96	-0.36	-4.23	0.34	139	143	192	34	233	6/86 - 12/05
Energy Inflation	0.99	-1.18	-13.27	0.12	51	288	178	192	287	1/67 - 12/05
Transportation Inflation	0.96	0.10	1.15	0.26	288	229	178	97	192	1/67 - 12/05
Oil Spot Price	0.89	-1.92	-20.73	0.33	51	229	38	184	45	1/67 - 12/05
Jet Fuel Spot Price	0.86	-1.42	-15.77	0.53	229	64	174	145	255	4/90 - 12/05
Diesel Fuel PPG*	0.99	-1.08	-12.24	0.10	258	82	123	229	245	3/94 - 12/05
Aggregate Inflation	0.97	0.13	1.56	0.23	229	88	287	104	162	1/67 - 12/05
S&P 500	0.70	-0.10	-1.20	0.62	228	229	304	297	267	1/67 - 12/05
Notes:										
Weights (0,1)										
*Best solution in 10th generation; convergence not guaranteed										

Table 7
MUTUAL FUNDS

Monthly Out-of-Sample Results for Ten Random Mutual Funds Using Annually-Established Policy
Validation Period: January-December 2007
Out-of-Sample Period: January-December 2008
Test Period Varies by Fund

Fund Symbol	$\frac{\sigma_H^2}{\sigma_{Target}^2}$	$\bar{H}$ (Monthly)	$\bar{H}$ (Annual)	Sharpe Portfolio	Sharpe Target	α Portfolio	α Target	$\rho_{Target, Portfolio}$	Assets 1	2	3	4	5	Target Beg – End (Mo/Yr)
ACMVX	0.424	3.518	51.425	0.274	-0.333	3.019**	1.502	0.777	20	154	157	219	304	4/04 - 12/08
BRGIX+#	0.519	2.230	30.305	-0.549	-0.559	-0.144	0.089	0.805	236	303	135	301	36	12/98 - 12/08
EXOSX	1.135	6.424	111.102	0.247	-0.556	2.015	-0.021	0.266	153	219	190	151	238	7/02 - 12/08
EXTAX#	0.636	3.635	53.485	-0.013	-0.514	0.995	0.252	0.676	120	127	53	231	219	4/98 - 12/08
FBALX	0.423	2.725	38.070	-0.134	-0.560	1.139**	0.025	0.804	8	43	120	160	249	1/87 - 12/08
FCNTX	0.638	2.480	34.167	-0.519	-0.600	-0.298	-0.289	0.643	77	153	168	250	291	5/89 - 12/08
FDVLX	1.477	8.937	179.319	0.376	-0.517	5.055	0.565	0.248	3	53	105	124	140	7/89 - 12/08
JMCVX+	0.795	2.664	37.093	0.004	-0.383	0.581	1.2575*	0.520	82	156	176	194	256	9/98 - 12/08
SPHIX	0.945	2.680	37.349	0.481	-0.399	0.441	0.857	0.280	82	188	257	273	277	11/94 - 12/08
WAGTX	1.061	4.611	71.767	-0.135	-0.620	2.979	-0.637	0.577	76	89	179	269	118	1/01 - 12/08

Notes: Weights (0,1)

*,** indicate significance at the 0.10 and 0.05 level, respectively

+ Best solution in 10th generation; convergence not guaranteed

Future values are unpredictable, so portfolio consists of unconditioned assets

This table summarizes the hedging performance for a portfolio of five assets identified by the Genetic Algorithm (GA) technique using the fitness function in equation (6) for the out-of-sample period December to January 2008. Column 1 shows the target mutual fund symbol. Column 2 shows the variance ratio of the hedged portfolio, *H*, which consists of a long position in the five-asset hedging portfolio and a short position in the

target mutual fund series. Column 3 (4) shows the average monthly (annualized) return of the hedged portfolio, *H*. Column 5 (6) shows the Sharpe Ratio for the five-asset hedging portfolio (target mutual fund). Column 7 (8) shows the Jensen's alpha from the single-factor CAPM for the five-asset hedging portfolio (target mutual fund). Column 9 shows the Pearson correlation between the target mutual fund series and the five-asset hedging portfolio. Columns 10-14 identify the investable assets that from the portfolio by their author-generated index numbers. Please see Appendix C for a list of the industries associated with these assets. The final column shows the relevant time series for the target mutual fund series. Below is the legend showing the stocks associated with the index numbers above.

Fund Symbol	**Fund Name**
ACMVX	American Century Mid Cap Value
BRGIX	Bridges Investment
EXOSX	Manning & Napier Overseas
EXTAX	Manning & Napier Tax Managed A
FBALX	Fidelity Balanced
FCNTX	Fidelity Contrafund
FDVLX	Fidelity Value
JMCVX	Janus Perkins Mid Cap Value T
SPHIX	Fidelity High Income
WAGTX	Wasatch Global Science & Technology

Table 8
Exchange Traded Funds (ETFs)

Monthly Out-of-Sample Results for Five Random ETFs Using Annually-Established Policy
Validation Period: January-December 2007
Out-of-Sample Period: January-December 2008
Test Period Varies by Fund

Fund Symbol	$\frac{\sigma_H^2}{\sigma_{Target}^2}$	$\bar{H}$ (Monthly)	$\bar{H}$ (Annual)	Sharpe Portfolio	Sharpe Target	α Portfolio	α Target	$\rho_{Target, Portfolio}$	Assets 1	2	3	4	5	Target Beg – End (Mo/Yr)
EWC	0.834	4.393	67.508	-0.281	-0.448	0.309	0.932	0.566	158	266	4	111	212	4/96 - 12/08
DIA+	0.390	2.006	26.908	-0.407	-0.607	0.300	-0.342	0.817	149	241	42	257	226	1/98 - 12/08
IWD	0.508	2.550	35.286	-0.263	-0.616	1.017	-0.319	0.709	247	128	177	93	234	5/00 - 12/08
IXN	0.149	1.735	22.924	-0.357	-0.519	1.109	0.356	0.923	102	202	103	174	32	11/01 - 12/08
IJT+	0.658	2.006	26.914	-0.355	-0.403	-0.119	1.384*	0.599	245	236	93	3	71	8/00 - 12/08

Notes:
Weights (0,1)
*indicates significance at the 0.10 level
+ Best solution in 10th generation; convergence not guaranteed

This table summarizes the hedging performance for a portfolio of five assets identified by the Genetic Algorithm (GA) technique using the fitness function in equation (6) for the out-of-sample period December to January 2008. Column 1 shows the target ETF symbol. Column 2 shows the variance ratio of the hedged portfolio, *H*, which consists of a long position in the five-asset hedging portfolio and a short position in the target ETF series. Column 3 (4) shows the average monthly (annualized) return of the hedged portfolio, *H*. Column 5 (6) shows the Sharpe Ratio for the five-asset hedging portfolio (target ETF). Column 7 (8) shows the Jensen's alpha from the single-factor CAPM for the five-asset hedging portfolio (target ETF). Column 9 shows the Pearson correlation between the target ETF series and the five-asset hedging portfolio. Columns 10-14 identify the investable assets that from the portfolio by their author-generated index numbers. Please see Appendix C for a list of the industries associated with these assets. The final column shows the relevant time series for the target ETF series. Below is the legend showing the stocks associated with the index numbers above.

ETF Symbol	ETF Name
EWC	iShares MSCI Canada Index
DIA	SPDR Dow Jones Industrial Average
IWD	iShares Russell 1000 Value Index
IXN	iShares S&P Global Technology
IJT	iShares S&P SmallCap 600 Growth

Appendix C
Stock Numbers, Tickers, and Industries

Number	Ticker	Industry
1	SUN	Oil & Gas
3	ABL	Rubber & Plastics
4	ABT	Pharmaceuticals
8	AEE	Diversified Utilities
10	AIP	Paper Products
11	AIT	Industrial Equipment
13	ALK	Airlines
15	AMR	Airlines
16	AP	Industrial Machinery
20	ASA	Financial
21	ASH	Chemicals
24	AVP	Personal Products
25	AVT	Electronics
30	BAX	Medical Supplies
32	BCE	Telecommunications
34	BDK	Machine Tools & Equip
36	BFA	Beverage
37	BFB	Beverage
38	BGG	Industrial Machinery
40	BMY	Pharmaceuticals
41	BP	Oil & Gas
42	BRN	Oil & Gas
43	BWS	Textiles
44	CAS	Materials Wholesale
45	CAT	Heavy Equipment
46	CBE	Conglomerate
48	CEG	Electric Utilities
49	CEM	Chemicals
51	CFS	Management Services
53	CHG	Diversified Utilities
56	CMC	Steel & Iron
64	CR	Conglomerate
66	CSC	IT Services
70	CUB	Science Instruments
71	CUO	Building Materials
72	CVR	Auto Manufacturing
76	DBD	Business Equipment
77	DD	Chemicals

Number	Ticker	Industry
81	DOW	Chemicals
82	DPL	Diversified Utilities
83	DTE	Electric Utilities
84	DUK	Electric Utilities
86	EDE	Electric Utilities
87	EGN	Gas Utilities
88	EIX	Electric Utilities
89	EK	Photo Equipment
90	EML	Tools
93	ESP	Electronics
97	F	Auto Manufacturing
102	FMC	Chemicals
103	FO	Home Furnishings
104	FOE	Chemicals
105	FPL	Electric Utilities
108	GAM	Financial
111	GD	Aerospace/Defense
113	GIS	Food
114	GLW	Communication Equip
117	GNI	Steel & Iron
118	GR	Aerospace/Defense
120	GV	Heavy Construction
122	GY	Conglomerate
123	HAL	Oil & Gas
124	HE	Electric Utilities
127	HL	Silver Mining
128	HNZ	Food
132	HPQ	Computer Systems
135	HSC	Steel & Iron
137	HUBA	Electronic Equipment
138	HUBB	Electronic Equipment
139	IBM	Computer Systems
140	IDA	Electric Utilities
143	IMO	Oil & Gas
145	IR	Industrial Equipment
146	IRF	Semiconductors
149	JCP	Department Store
151	K	Food

Number	Ticker	Industry
153	KO	Beverage
154	KR	Grocery
156	L	Property/Casualty Ins
157	LDR	Research Services
158	LG	Gas Utilities
160	LMT	Aerospace/Defense
161	LUK	Lumber Production
162	LZ	Chemicals
168	MDP	Publishing
171	MHP	Publishing
172	MMM	Conglomerate
174	MOGB	Aerospace/Defense
175	MOT	Telecommunications
176	MRK	Pharmaceuticals
177	MRO	Oil & Gas
178	MSB	Financial-Land
179	MUR	Oil & Gas
184	NEM	Mining
185	NEU	Chemicals
186	NFG	Gas Utilities
187	NGA	Industrial Equipment
188	NI	Diversified Utilities
190	NOC	Aerospace/Defense
192	NR	Oil & Gas
194	NVE	Diversified Utilities
195	NXY	Oil & Gas
196	OGE	Electric Utilities
197	OKE	Gas Utilities
198	OLN	Synthetics
199	OMX	Business Equipment
200	OXM	Textiles
202	PAS	Food
203	PBI	Business Equipment
204	PBY	Auto Parts
212	PG	Personal Products
215	PKE	Circuit Boards
216	PKI	Medical Supplies
219	POM	Electric Utilities
226	ROG	Rubber & Plastics
227	ROH	Chemicals

Number	Ticker	Industry
228	ROL	Business Services
229	RONC	Manufacturing
230	RRD	Business Services
231	RSH	Electronics Retail
233	S	Wireless Comm
234	SCG	Utilities
236	SCX	Manufacturing
237	SEB	Meat Products
238	SGP	Healthcare
241	SJM	Food
243	SLB	Oil & Gas
245	SLI	Electronics
247	SNR	Electronics
249	SO	Electric Utilities
250	SPA	Electronics
251	STL	Banking
253	SWK	Machine Tools & Equip
254	SXI	Industrial Equipment
255	SYNL	Steel & Iron
256	TE	Electric Utilities
257	TEG	Diversified Utilities
258	TJX	Department Store
263	TPL	Financial-Land
266	TSTY	Food
269	TXT	Conglomerate
272	UIS	IT Services
273	UL	Food
275	UST	Tobacco
277	UVV	Tobacco
287	WEDC	Semiconductors
288	WEN	Fast Food
289	WEYS	Textiles
291	WGL	Gas Utilities
297	WSC	Accident & Health Ins
301	XEL	Electric Utilities
303	ZAP	Holding Company
304	Long Bond	Long Bond
305	Short Bond	Short Bond
306	T-Bill	T-Bill