Essays on Inflation, Real Stock Prices, and Extreme Macroeconomic Events

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To my family

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"Now this is not the end. It is not even the beginning of the end. But it is, perhaps, the end of the beginning."

(Sir Winston Churchill, Speech in November 1942)

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ABSTRACT

This thesis examines the negative correlation between inflation and real stock prices. First, using an Emerging Market data sample, I find robust evidence for inflation imposing real costs on the economy, in particular by decreasing firms' real earnings as originally claimed by Milton Friedman. The results limit the need for behavioral explanations. Second, I suggest that increasing inflation led to lower real stock prices as the probability of experiencing a stagflation episode increases (rare-event premium). Third, I test whether macroeconomic data provide evidence for a positive correlation between inflation and uncertainty, and between inflation and the price of risk (i.e. relative risk aversion), as suggested in the literature. Fourth, I introduce a historical case, Germany between 1870 and 1935, and show that it is the rare-event premium, not money illusion, what drives the negative relation between inflation and stock prices. The fifth chapter is a separate work on emerging markets financial contagion.

RESUMEN

La presente tesis estudia la correlación negativa entre inflación y precios reales de las acciones. En primer lugar, utilizo una muestra de países emergentes, y muestro evidencia de que la inflación impone costos reales en la economía, en particular al disminuir los beneficios de las empresas, tal como sugiriera originalmente Miton Friedman. Estos resultados limitan la necesidad de explicaciones del tipo 'behavioral'. Segundo, sugiero que la inflación decrece los precios reales de las acciones dado que la probabilidad de sufrir estanflación en el futuro crece con la tasa de inflación (premio evento-extremo). Tercero, testeo si la evidencia macroeconómica respalda la relación positiva entre inflación e incertidumbre, y la relacioón entre inflación y el precio del riesgo (avesión relativa al riesgo). Cuarto, presento un estudio histórico, Alemania entre 1870 y 1935, para mostrar que es el premio por evento-extremo, y no illusion monetaria, lo que conlleva la correlación negativa entre inflación y precios reales de acciones. El ultimo capítulo discute contagio en países emergentes.

FOREWORD

This dissertation includes five chapters, of which the first four chapters are dedicated to investigate the relationship between inflation and real stock prices. The last chapter is a separate work on Emerging Market financial contagion.

In the last 30 years the relation between inflation and real stock prices has been widely discussed in the literature. If stocks are a claim on real capital, the covariance between real stock prices and inflation should be zero. However, the empirical findings show a robust negative correlation between inflation (realized, expected and unexpected) and real stock prices. This is known as the 'stock price-inflation puzzle'.

A number of models have been developed to explain the 'stock price-inflation puzzle'. However, the lack of robust empirical evidence for the different channels suggested in the literature has led the authors to support behavioural factors. The behavioural approach mostly relies on money illusion: investors confuse nominal and real discount rates. Thus, given future real cash flows, higher inflation leads to higher discount rates (nominal interest rates), and therefore to lower stock prices (cf. Modigliani and Cohn, 1979; and Campbell and Vuolteenaho, 2004).

In Chapters 1 to 4, I introduce empirical evidence that questions the need to build on money illusion and related behavioural approaches. Moreover, I discuss how the negative correlation between inflation and real stock prices could be explained by agents discounting future rare macroecomic events (rare-event premium). I also test whether the macroeconomic data back some of the common assumptions that the literature has recently made on the inflation and risk relationship. Finally, I show that the rare-event premium hypothesis is more robust than the behavioural hypothesis.

In the first chapter of this dissertation work, I argue that the lack of empirical evidence for the real channels suggested in the literature might result from the limiting characteristics of the inflation data on developed countries. I test for the presence of real channels by using data on Emerging Markets. These have the advantage of substantial variation of inflation rates both across time and countries. The results give support to the idea of inflation imposing real costs on the economy, in particular by decreasing firms' real earnings as originally claimed by Milton Friedman (1971, 1977). The results limit the need for behavioural explanations.

In Chapter 2, I work on an explanation for the positive correlation between inflation and risk. In this framework, realized inflation is used as a proxy for the probability of a rare event, namely high inflation accompanied by stalling or negative economic growth (stagflation). When agents observe increasing inflation rates, they perceive an increase in the probability of experiencing a stagflation episode in the future. Consequently, agents demand a higher premium. The model predicts a positive relation between the correlation of inflation and real stock prices, and both uncertainty and risk aversion. I test the model implications for the US and Germany, and find empirical support for the model predictions.

The third chapter is dedicated to test whether macroeconomic data provide evidence for a positive correlation between inflation and uncertainty, and between inflation and the price of risk (i.e. relative risk aversion). It has been suggested that the 'real stock prices-inflation puzzle' could be explained by an unconditional positive relation between inflation and risk (cf. Brandt and Wang, 2003; and Bekaert and Engstrom, 2010). The results show that there is a strong relation between inflation and uncertainty, but only for inflation levels above 10 percent (annualized rates). Also, the positive relation between inflation and risk aversion is not robust for inflation regimes below 10 percent, or above 50 percent. However, I find evidence for a monotonic relation between inflation and stagflation risk premium (rare-event premium) discussed in Chapter 2.

Chapter 4 introduces a historical case, German economy between 1870 and 1935, to show that it is the rare-event premium, not money illusion, what drives the negative relation between inflation and stock prices. While testing for money illusion is an elusive quest, I discuss two cases that help to differentiate the rare-event premium from money illusion. First, the rare-event premium is state-dependent while money illusion is not. Second, inflation must belong to the investment set (understood as the set of all dimensions relevant to an investment decision) for the rare-event premium explanation to make sense. However, this is not true in the case of money illusion. Even if price changes are not giving any information on future inflation rates, agents will continue to use nominal discount rates instead of real discount rates. Using data on the Gold Standard period, as well as the inflation period (1921-23), I find evidence supporting the rare-event premium explanation.

Finally, the last chapter of the dissertation is dedicated to contagion on Emerging Markets. I show that the US stochastic discount factor (SDF) is behind the return comovement increase in EM assets (e.g. sovereign debt spreads) and US assets (e.g. corporate spreads). Therefore, Emerging Market assets are not good for portfolio diversification during developed market turmoil periods. I use the American Fama-French factors to proxy for US SDF, and show that they explain a relevant share of sovereign spreads. Moreover, it is shown that volatility in the US financial markets is a necessary condition for the existence of contagion in Emerging Markets.

Contents

1 Inflation, Real Stock Prices and Earnings: Friedman Was Right

1.1 Introduction

When inflation increases, stocks fall. Many authors have tried to explain this fact by the performance of real variables. To date, there are no studies showing that real earnings suffer significantly during inflation episodes[1]. I suggest that the lack of empirical evidence might result from the limiting characteristics of the data on developed countries. In this paper I test for real channels by using data on Emerging Markets. These have the advantage of substantial variation of inflation both across time and countries. The results give support to the idea of inflation imposing real costs on the economy, in particular by decreasing firms' real earnings as originally claimed by Friedman (1971, 1977). At the same time, the results limit the need for behavioral explanations, e.g. money illusion, as initially suggested by Modigliani and Cohn (1979)[2].

In this paper, I test for the existence of three real channels in the case of Emerging Markets (henceforth abbreviated as EMs). First, the direct impact of realized inflation on future real earnings growth rates is tested, controlling for the business cycle and also for non-linearities. Second, the relation between inflation and risk is examined in an indirect way. That is, I show that the correlation between

[1]Empirical research consistently finds a negative relation between inflation and real stock prices (i.e. earning yield or dividend yield), e.g. Campbell and Shiller (1988a); Barr and Campbell (1996); Pennacchi (1991); Campbell and Ammer (1993); Amihud (1996) ; Campbell and Shiller (1996); Duarte (2010). Related to this, a number of papers study the negative correlation between bond and stock yields, i.e. Thomas and Zhang (2008); Asness (2002); Bekaert and Engstrom (2010a); Zhang and Thomas (2008); and Durre and Giot (2007).

[2]Main papers supporting money illusion are Modigliani and Cohn (1979); Campbell and Vuolteenaho (2004); and Brunnermeier and Julliard (2006), this last one for real estate prices instead of real stock prices.

stock prices and inflation is significantly higher in recessions (high risk aversion and uncertainty) than in expansions (low risk aversion and uncertainty), while the impact of inflation on real earnings does not show significant variations in recessions when compared to expansion periods. Third, I test for inflation decreasing the real value of nominal liabilities, therefore increasing real stock prices. Note that this last real channel would imply a positive correlation between inflation and real stock prices, conditional on the firm's leverage.

Panel estimations are performed instead of the time-series studies present in the literature. This allows me to exploit the rich variation in country, time, and sector, present in the EM sample. The empirical strategy also aims to capture short-term variations, since even the studies disputing the long-run relation between inflation and stock prices (or bond and stock yields) find support for a short-term relation (e.g. Durre and Giot 2007). Therefore, the data frequency for the estimations is monthly[3]. I perform three different sets of estimations, where the panel unit of analysis is the firm, market and sector, respectively. The point is to avoid potential aggregation biases that might otherwise drive the results. In the first specification, the panel unit is each firm in the sample. In this case, the real stock price for each firm is the earning price ratio. In the second specification, the panel unit is the market-portfolio. For that, capital-weighted earnings price ratios are used as real stock prices. In the third specification, the panel unit is the sector-portfolio. In this last case, capital-weighted sector earnings price ratios are used as real stock prices. The estimation is adapted to the panel unit: standard and long panel estimations are implemented when working with stocks and portfolios as the panel unit, respectively. The results are robust to the use of different panel units[4].

[3]It is worth to note that the results remain unaltered when working with quarterly data.

[4]Concerns on using monthly frequency for earnings are addressed by using

The literature identifies two real channels under which inflation negatively influences real stock prices. First, inflation decreases future real earnings growth rates as early papers by Friedman (1971, 1977), and Fama (1981) suggest. For example, inflation hampers intertemporal capital allocation (e.g. Aruoba et al. 2009; Chiarella et al. 2007; Brennan and Xia 2002), or acts as a distortionary tax (e.g. Cooley and Hansen 1989; Chari et al. 1996). If these frictions are present, inflation induces a decrease in future real earnings, driving the stock price downward. However, there is as yet no empirical support for a negative correlation between inflation and future real earnings. Moreover, some studies point out that the correlation between inflation and real earnings (dividends) is perhaps even positive (e.g. for the US: Asness, 2003; Feinman, 2005; Campbell and Vuoltenahoo, 2002; and Spyrou, 2004 for emerging countries).

The second real channel relates inflation to risk: inflation correlates positively with risk aversion as in Brandt and Wang (2003); or inflation correlates positively with both risk aversion and uncertainty as in Bekaert and Engstrom (2010a)[5]. As risk increases, investors demand higher expected returns, driving real stock prices downward. Bekaert and Engstrom (2010a) find that the covariance of inflation and risk can explain almost half of the covariance between inflation and real stock prices. However, in the same paper, the authors cannot find a significant covariance between inflation and real earnings growth rates.

The third real channel suggested in the literature is the leverage channel. Under imperfect capital markets, real stock prices may also correlate positively with inflation. Ritter and Warr (2002) suggest

quarterly data. Also, I use year on year as well as quarter on quarter variations when working with earning growth rates.

[5]Bekaert and Engstrom (2010a) show that inflation is positively related both to risk aversion and uncertainty in the US. They use a time-varying risk aversion measure based on Campbell and Cochrane (1999) and the variance of GDP growth forecasts from the Professional Forecasters Survey as a measure of uncertainty.

that inflation can affect equity value by decreasing the real value of nominal liabilities. For a given expected real cash flow (i.e. firm's value), inflation decreases real debt, increasing the equity value. The authors do not find evidence of the leverage channel for the US stock market, and refer to this as a valuation error (i.e. debt capital gain error). Note that when the leverage effect is incorporated, the correlation between real stock prices and inflation may even be positive. This happens if the variation in the real stock price owing to inflation eroding the real value of debt is higher than the variation generated by lower real earnings growth rates and higher risk aversion[6].

The closest empirical study to the present one is that by Spyrou (2004), since this is the only paper that tests the relation between inflation and stock returns in EMs. The author studies the relation in a time series framework, the sample including nine EMs for the period 1989-2000. One key point is that the author works only with nominal returns. His results show that in four countries there is a negative relation between inflation and nominal returns. However, he concentrates on the cases in which inflation correlates positively with nominal returns, and argues that in those cases there is a positive relation between inflation (CPI) and industrial production. The main problem with this approach is that the author is not controlling for real activity when estimating the covariance between inflation and nominal returns. The estimations then suffer from a strong misspecification, as discussed by Fama (1986).

This paper is structured in the following way. Section 2 describes the data sample. Section 3 introduces the empirical strategy and present the results regarding the correlation between inflation and stock prices, and the presence of real channels. Section 4 comple-

[6]The leverage channel may help us to understand what drives up stock prices (conditional on expected future dividend growth rate and discount rates) during hyperinflation or very-high-inflation periods (see Chapter 4 and Pereira-Garmendia 2008).

ments the previous analyses by providing new insights at a sector level. Section 5 includes the discussion and concluding remarks.

1.2 Data Description

The data sample spans the period January 1986 to December 2007, on a monthly frequency, for 15 EMs. Earnings price ratios -earning yields- are used as (the inverse of) real stock prices. Trailing earning yields are used, that is, the last 12-month accumulated earnings over the stock price. The data is from the Emerging Market Database (EMDB). The reason for working with earnings price ratios instead of price-earnings is that the price-earning relation is discontinuous when earnings are close to zero. When creating portfolios, I aggregate firm earning yields weighting by the firms' capital. Both sector and country portfolios are created. Capitalization data comes also from EMDB.

Different aggregation levels for sector data are available. There are 60 sectors in the sample at the lowest level of sector aggregation. These sectors are, at a time, aggregated in a 22-sector ranking, and finally, the highest aggregation level includes ten sectors: Consumer Discretionary, Consumer Staples, Materials, Industrials, Financials, Energy, Utilities, Information Technology, Telecommunication Services and Health Care.

For leverage, the market debt over capital ratio is used. The data is from Bloomberg, at a firm level, for the years 2006 and 2007[7]. Since leverage data is only available for 2006 and 2007, I construct sector leverage at lowest level of sector aggregation available (60 sectors). In order to construct the series spanning the period 1986-2007,

[7]While some papers use the Rajan and Zingales (1998) external financial dependence ratios in order to test financial development, in my case these ratios are not informative, since it is the ratio of debt to equity the one that has implications for the effect of inflation, not the overall external financing (which is the sum of both equity and debt).

I weight each firm leverage ratio using capitalization as weights, thus creating variation in time for the sector-leverage series. A key issue immediately arises. While it would be optimal to have the actual leverage data for the sample period, due to data limitations, only two years of leverage data is available. In order to create variation in time for 21 years, the assumption placed is that the leverage ordering between sectors does not vary in time. For example, if leverage of Materials is higher than Industrials in 2006-07, then this remains true for the whole period 1986-2007. In Table 1.2 the leverage at highest sector aggregation (10-sector aggregation) is presented for the countries in the final sample. Note that, sorting per sector, Utilities is the sector with highest leverage, followed by Financials, while the sectors with lowest leverage are Information Technologies and Heath Care.

Inflation data at a monthly frequency is from IMF IFS. The CPI indices are seasonally adjusted, as to avoid noise in the monthly inflation rates. Figure 1.1 shows the time series for the first, second and third inflation quartile on the left axis, and the fourth quartile on the right axis. Inflation in EMs follows a similar pattern to developed markets. During the 80s, monthly inflation was high and volatile (Great Inflation). After mid-90s, inflation decreased considerably and has remained low and stable since then. Nonetheless, the variation present in EMs -both cross-country and in time- is very high. During the sample period, some of the countries included in the sample experienced long periods of high inflation (higher than 50 percent annual inflation); hyper-inflations (higher than 50 percent monthly inflation); and also long periods of inflation below five percent (in particular the period 2001-2007). It is worth to emphasize that, although in eight percent of the sample the monthly inflation is negative (deflation), only Argentina shows a sequence of consecutive deflationary months from 1999 to 2002 (22 of 36 months show negative inflation figures). An interesting feature of the sample is the weak relation between deflation and economic contractions. Of the 278 months in which inflation is negative, only in 39 GDP is contracting. Moreover, real stock prices are on average higher on deflation periods.

In the estimations, among different controls, I include real GDP growth rates. Given that the highest frequency for GDP is quarterly, monthly series are created in the following way: a) giving the same figure for all the months in a quarter; and b) interpolating quarterly figures into monthly figures. The results are robust to both approaches. Controlling for the economic cycle is also relevant in the specifications. For that, a dummy variable is defined, taking value one if the economy is in recession and zero otherwise. A recession is defined in two different ways: a) whether the real GDP variation is negative; and b) whether the real GDP index is below a trend calculated with the Hoddrick Prescott filter. Again, the results do not change whether using measures a) or b). Other control variables included in the estimations are capital inflows, current account deficits, and international reserve variations. All these series are from IMF IFS database.

I also classify periods of currency, banking and twin crisis. The periods are chosen in concordance with Laeven and Valencia (2008) database. A currency-crisis starts in the month showing a significant increase[8] in depreciation rate vis-à-vis US dollar and ends in the month in which depreciation peaks. For banking-crisis, the starting month is taken from Laeven and Valencia (2008) database, and the ending month corresponds to the month in which banks deposits stabilize. Finally, a Twin-crisis is defined for those periods in which both currency and banking-crisis are observed. Sovereign debt-crisis periods were not included since only the case of Argentina 2002 is included in the sample.

[8] More than two standard deviations from the last 24-month window.

1.3 Method and Results

Panel estimations are performed in order to benefit from the variation in country, time, and sector present in the EM sample. The empirical strategy also aims to capture short-term relationships, since even the papers disputing the long-run relation between inflation and stock prices (or bond and stock yields) find support for a short-term relation. Therefore, the data frequency for the estimations is monthly[9]. I perform three different sets of estimations, where the panel unit of analysis is the firm, market and sector, respectively. The point is to avoid potential aggregation biases that might otherwise drive the results. In the first specification, the panel unit is each firm in the sample. In this case, the real stock price for each firm is the earnings price ratio. In the second specification, the panel unit is the market-portfolio. For that, capital-weighted earnings price ratios are used as real stock prices. In the third specification, the panel unit is the sector-portfolio. In this last case, capital-weighted sector earnings price ratios are used as real stock prices.

The estimation is adapted to the panel unit: standard and long panel estimations are implemented when working with stocks and portfolios as the panel unit, respectively. When working with the stock panel unit, it is possible to control for serial correlation in the error using cluster-robust standard errors. However, when the number of observations in time is large relative to the number of cross-section units, it is necessary to specify a model for serial correlation in the error. Therefore, when working with portfolios long panel estimations are performed[10]. I estimate a model in which the error term can be correlated and heteroskedastic, by performing a panel FGLS estimation: $y_{it} = x_{it}^{'}\beta + u_{it}$; where the error is term u_{it} is modeled

[9] It is worth to note that the results are robust when working on a quarterly frequency.

[10] See Cameron and Trivedi (2009).

as an AR(1) process $u_{it} = \rho_i u_{it-1} + \varepsilon_{it}$; allowing for heteroskedasticity $E(u_{it}) = \sigma_i^2$; $E(u_{it}, u_{jt}) = 0$; and ε_{it} are serially uncorrelated: $E(\varepsilon_{it}, \varepsilon_{it-1}) = 0$. In all cases, the estimations are done for unbalanced panels.

1.3.1 Real Stock Prices and Inflation

First, I test if the negative correlation between realized inflation and real stock prices is present in EMs[11]. For that matter, the impact of lagged inflation on the earning yield is estimated. Since the earning yield is constructed with trailing earnings, most of the high frequency variations obey to changes in the stock price. At the same time, I also test if the leverage effect is present in the case of EMs, as discussed in Ritter and Warr (2002). Moreover, I test if it is the inflation rate or inflation volatility what drives the correlation with lower real stock prices. Finally, asymmetries in the correlation are tested. In particular, the correlation is tested when the economy suffers GDP contractions, and different crisis types: banking, currency or twin crisis.

In order to test the correlation between inflation and real stock prices, I regress the earning yield as the dependant variable[12], and present two different set panel estimations in this section. In the first specification, the panel unit is each firm (stock) in the sample. In the second specification, the panel unit is the market-portfolio. For that, capital-weighted earnings price ratios are used as real stock prices. The results for the third specification, the sector-portfolio specification, are discussed in Section 5.

The benchmark specification for the stock specification is

[11] The paper is meant to analyze the correlation of stock prices and realized inflation. However, I also investigate the correlations of stock prices and expected (unexpected) inflation. I will briefly comment on these results in the corresponding sections.

[12] Panel unit root tests for stock yields reject the existence of unit roots.

$$\frac{E}{P}_{ijt} = \alpha_0 + \alpha_1 \pi_{jt-1} + \alpha_2 \triangle gdp_{jt} + X_{ijt}^{'} \lambda + e_{ijt}$$

$$t = 1, ..., T, \quad j = 1, ..., J, \quad i = 1, ..., I$$

where the dependent variable $\frac{E}{P}_{ijt}$ is the earnings yield corresponding to firm i of country j at time t; π_{jt-1} is the month on month inflation rate of country j at time $t-1$; $\triangle gdp_{j,t}$ is real GDP growth rate in the next quarter i; and a set of other controls $X_{i,j,t}$. Stock and market dummy variables are included when noted. I cluster at a market level in order to control for autocorrelation in the panel errors.

The results are reported in Table 1.4. In Panel A, specifications (i)-(ii), the earning yield is explained by the lagged month on month inflation rate. In all cases the estimated coefficient *(INF)* is positive and significant, implying that higher inflation drives real stock prices downwards. In order to control for the Fama proxy hypothesis, specifications (iii)-(iv) include the actual GDP growth rate in the following quarter[13]. The results show that inflation is still positive and significant, while the estimated coefficient for the expected growth proxy is positive but not significant. Note that in the last set of estimations the number of observations decrease substantially, from more than 126,000 to almost 70,000. The reason for this decrease in the number of observations is the lack of quarterly national accounts data[14].

In Panel B of the Table 1.4, the effect of leverage on the inflation-stock price relation is tested.The variable DEBT is included in the model, which is the firm leverage (defined for the sector to which the firm belongs).

The model to be estimated is

[13]For the period data on the expected economic growth is not available. I use, as a proxy, the actual GDP growth rate in the next quarter.

[14]Note that the sample for the second set of regressions is "more recent" in time than the previous set. To check if there is a sample bias when comparing both results, I repeat estimations (i)-(ii) using the same sample as in (iii)-(iv). The results hold, since inflation coefficient is still positive and significant.

$$\frac{E}{P}_{ijt} = \alpha_0 + \alpha_1 \pi_{jt-1} + \alpha_2 \triangle gdp_{jt} + \alpha_3 \pi_{jt}\, debt_{jt} + \alpha_4 debt_{jt} + e_{ijt}$$

$$t = 1, ..., T, \quad j = 1, ..., J, \quad i = 1, ..., I$$

where *debt* accounts for the market debt to capital ratio, and $\pi_{jt}\, debt_{jt}$ is the interaction term between inflation and leverage. The model is aimed to test if the stock price of firms with higher leverage should benefit from inflation, due to a decrease in the real debt value of the firm ($\alpha_3 < 0$). The results in regressions (i)-(iii) show that the leverage channel is significant. The coefficients for the cross term *INF**DEBT are negative and significant in the three regressions, implying that when inflation increases, real stock prices increase conditional on leverage. The coefficients for inflation are still positive and higher than in the Panel I estimations. Note that the inflation coefficients estimated in Panel A are the combination of both the coefficients for inflation and for the interaction term of inflation and debt in Panel B.

Regressions (iv) and (v) in Panel B test whether there are asymmetric effects in economic expansions and contractions. I include a dummy variable (*REC*) taking the value one when GDP decreases and zero otherwise is included in the regressions. At a stock level, the asymmetric effect is not significant when including the leverage channel, since *INF**REC is not significantly different from zero, implying no significant differences for the inflation-real stock price relation whether the economy is contracting or expanding.

The second panel specification, the market-portfolio specification, takes each market as the panel unit. The market earnings price is regressed on monthly inflation. In this case, the benchmark regression is

$$\frac{E}{P}_{jt} = \alpha_0 + \alpha_1\, \pi_{j-1} + \alpha_2 \triangle gdp_{t,t+3} + \alpha_3\, \pi_{jt} debt_{jt} + \alpha_4\, debt_{jt} + e_{jt}$$

$$t = 1, ..., T, \quad j = 1, ..., J$$

where the dependent variable $\frac{E}{P}_{jt}$ is the earnings yield corresponding to market j at time t; π_{jt-1} is the month on month inflation rate of country j at time $t-1$; $\triangle gdp_{j,t}$ is the following quarter real GDP growth rate. Market dummy variables are included when noted. I also include the market debt over capital ratio and the cross-term of inflation times the debt ratio (to test the leverage channel).

In Table 1.5, the estimation results are reported. In specification (i), the inflation coefficient remains significant and positive. Thus, higher inflation correlates with lower stock prices. The leverage channel is again significant. Conditional on the debt to capital ratio, higher inflation rate correlates with higher real stock prices. In models (ii)-(iv), I test if asymmetric effects are present. While for the stock approach there were not significant asymmetries, a different picture emerges when working with market earning yields. The results show that a relevant share of the variance is explained when the economy is contracting. When the economy is expanding, inflation coefficient is positive but not significant when the leverage channel is included (specifications (ii) and (iv)). Thus, most of the unconditional correlation between inflation and real stock prices is explained in contraction periods, when both risk aversion and uncertainty are high. This last result is in line with the recent paper by Bekaert and Engstrom (2010). For the leverage channel, both during expansion and contraction periods the coefficients are negative and significant, implying that inflation increases stock prices by decreasing real debt.

1.3.1.1 Real Stock Price, Inflation Level and Inflation Volatility

One potential explanation for the correlation between inflation and real stock prices is that it is inflation volatility, not the inflation level, what drives the correlation. Higher inflation volatility increases uncertainty, thus driving stock prices lower. In order to test if inflation volatility is indeed the relevant dimension in order to explain the correlation between inflation and stock prices, I include in the model specification inflation volatility as an independent variable (*VOLATILITY*). The series are estimated by fitting an AR(1)-GARCH(1,1) model to the monthly inflation series[15]. Inflation conditional volatility is included as an independent variable in the specification, in order to check if the inflation level remains to be significant.

The results from including inflation conditional volatility as an independent variable are presented in Table 1.6. In all specifications, the coefficient for inflation volatility (*VOLATILITY*) is not significant, and shows a positive sign, implying lower stock prices. However, inflation level (*INF*) is positive in all specifications, but only significant when controlling for leverage. In specification (iv), the interaction term of volatility and debt is included (*VOLATILITY*DEBT*), finding no significant effect. The conclusion is that it is the inflation level, not volatility, what drives the correlation between earnings price ratios and realized inflation.

1.3.1.2 Asymmetric Crisis Effects

Another interesting dimension to analyze are the possible asymmetric effects when the economy is facing different crisis. Given the number of crisis-events in the EM sample, it seems almost naturally to test if the correlation experience significant changes when conditioning on crisis. I analyze the correlation of inflation and price-earning ratios for different crisis-typologies: currency, banking and twin crises. For that matter, the crisis dummy variable is interacted with the inflation rate (*INF*CURR, INF*BANK*, and *INF*TWIN*) and leverage (*INF*DEBT*CURR, INF*DEBT*BANK,* and *INF*DEBT*TWIN*). A currency-crisis starts in the month showing a significant increase in depreciation rate (vis-a-vis US dollar) and ends in the month in which depreciation peaks. For banking-crisis, the starting month is

[15] I also use this estimation setup to decompose realized inflation into its expected and unexpected components.

taken from Laeven and Valencia (2008), and the ending month corresponds to the month in which banks deposits stabilize. Finally, twin-crisis months are those for which both currency and banking crisis are observed.

The results are in Table 1.7. Column (i) presents the results from regressing earning yield on inflation, leverage and its cross-term for in all periods. Column (ii) shows the results for currency-crisis periods, Column (iii) for banking-crisis, Column (iv) for twin-crisis and, finally, Column (v) for banking and currency crisis periods that do not correspond to twin-crisis months.

For all periods (first row of the estimations), inflation coefficient *(INF)* is always positive and significant: higher inflation correlates with lower stock prices. The interaction term *INF*DEBT*, i.e., leverage channel, presents a negative and significant coefficient in all five specifications: stock prices of more indebted firms increase when inflation rises. Note that $DEBT$ shows a negative coefficient. Actually, this is true in the five specifications, but in all cases the coefficient is not significantly different from zero.

For currency-crisis periods, Column (ii), the conditional earning yield (*Currency_crisis*) is 0.0371 higher than during non-currency crisis periods, implying a 29.8 percent stock price decrease in annualized terms. The inflation coefficient for non-currency-periods (*INF*) is positive and very significant. For times of currency-crisis spell, an increase in the inflation rate correlates with a stronger decrease in the stock price (*INF*CURR* is highly significant). However, the effect is minimized if the firm is leveraged. The interaction term of inflation and debt (*INF*DEBT*CURR*) presents a strongly significant negative coefficient when currency-crisis months. Consequently, more leveraged firms tend to net out the direct effect of inflation on stock prices.

For banking-crisis periods - Column (iii) - the results show that when inflation rises, stock prices do not decrease more than in non-banking-crisis periods. Both the interaction term between inflation and banking-crisis dummy *(INF*BANK)* and the interaction term between inflation, leverage and the dummy *(INF*DEBT*BANK)* are not significantly different from zero. This result is interesting when compared with the currency-crisis periods, where stock prices strongly decrease and leverage is key to understand which firms are more punished by the market.

A potential caveat of the previous analyses is that for some periods a country may suffer from both a currency- and a banking-crisis. In order to control for these particular periods, I define a twin-crisis as a period in which the country is suffering both types of crises at a time. The estimation in Column (iv) analyzes twin-crisis. Conditional on twin-crisis, the earning yield increases by 0.0508, implying a 36.5 percent stock price decrease in annualized terms. The results show that the effect of both currency and banking crises seems to net out, being the conditional effects of inflation not significantly different from those under non-twin-crisis periods (*INF*TWIN* and *INF*DEBT**TWIN are not significant).

Finally, in Column (v), I analyze periods of non-contemporaneous currency and banking crisis. That is, crisis periods that are not twin-crisis periods. First, note that the differential effect on both the inflation and leverage effect for currency crisis is back in the picture. As in the analysis for currency crises in Column (ii), the interaction terms with the currency-crisis dummy *(INF*DEBT*CURR)* is strongly significant. The higher the leverage, the lower the stock price impact of inflation under currency crisis. Nota that for banking crisis periods this is not true, coherently with the findings in Column (iii).

1.3.2 Inflation and Real Earnings

Early papers by Friedman (1971, 1977) and Fama (1986) suggest that inflation imposes real costs on the economic activity. Inflation induces a decrease in future real earnings, driving stock prices downwards. If so, inflation at time *t* should be able to forecast lower real earnings in the next periods. While empirical evidence does not support the assumption for developed markets, I directly test this real channel in the case of EMs. Again, both the stock and market-portfolio specification estimations are discussed[16].

The results for the stock-approach are included in the first panel of Table 1.8. In the four specifications presented in the table, inflation (*INF*) correlates negatively with real earning variations. The results are robust when including a trend variable, fixed effects, and clustering the errors. In the second panel of Table 1.8 the results for the market-portfolio regressions are presented[17]. Contemporaneous as well as lagged inflation rates are always significant, with the only exception of two-month lagged inflation. The sign of the estimated coefficients is always negative: increasing inflation forecasts negative real earnings variations in the coming months. The estimated coefficients are rather stable for the three quarters included in the regressions. These coefficients imply a decrease in real earnings between 0.18-0.40 percent per one percent inflation increase[18]. On average, the inflation spell duration is about 12 months.

In Table 1.9, I test whether the relation changes if the economy is expanding or contracting. During contractions there is no significant differential effect of inflation on future real earnings, as INF*REC$_j$ are no significant, for j=1, 2, 3, 6, and 9 lags. Consequently, infla-

[16]Concerns on using monthly variations are addressed by using quarterly data, and year on year as well as quarter on quarter variations when working with earning growth rates.

[17]Results from the sector-portfolio approach are in line with the results presented in this section.

[18]In Aizenman and Marion (2009) an inflation of five percent is associated with an output cost during the inflation-disinflation cycle of about three percent of GDP for the US, which implies a cost of 0.60 percent on a monthly basis. The results for EMs show rather smaller implied inflation cost, between 0.18 and 0.40. While the comparison is not strictly correct, since one is measuring the impact on GDP and the other on aggregated earnings, both figures should be close, as in the present case.

tion drives real earnings growth rates downwards independently of the economic cycle. The estimated coefficients imply a real earning decrease between 0.15 and 0.40, similar to the results in Table 1.8. Finally, I explore asymmetric effects of inflation on real earning variations when the economy is suffering different types of economic crises: currency, banking and twin-crisis. As before, a dummy variable is created for each type of crisis: *Curr-Crisis, Bank-Crisis* and *Twin-Crisis.* The first part of Table 1.10 introduces the results for the crisis-conditional effects on real earnings growth rates. Note that Twin-Crisis is the strongest type of crisis, coherent with the effects of crisis on real stock prices. For currency-crisis, real earning growth rate decreases by 2.5 percent on a monthly basis; for banking-crisis 1.7 percent; and for twin-crisis 5.6 percent (26 percent; 19 percent; and 49 percent annualized decrease, respectively)[19]. Since crisis periods are contemporaneous to contractions periods, the results in Table 1.10 suggest that for the average crisis-period the correlation between inflation and real earnings growth rates should not be significantly different from the non-crisis periods correlation. Coherently, in specifications (ix)-(xii), no significant differential effect is captured for the inflation-real earning correlation during crisis-months. None of the variables *INF*CURR*, *INF*BANK* or *INF*TWIN* are significant. Inflation negatively affects real earnings, independently on the economic cycle and type of crisis. However, as discussed before, the correlation between inflation and real stock prices does vary in a different way conditional on the type of crisis. I find these results are indirect evidence supporting Beakaert and Engstrom (2010) claim that inflation correlates with higher risk aversion and uncertainty.

I conclude this section stressing the three main findings: i) there is a strong negative relation between inflation and future real earnings; ii) there is no significant difference when conditioning on the eco-

[19]The results remain similar when including GDP growth rates in the regressions.

nomic cycle (contractions and expansions); and iii) there is no significant difference when conditioning on crisis-types (currency, banking or twin crisis). Given that the inflation-real stock prices correlation does vary in a different way conditional on the business cycle and type of crisis, the results in ii) and iii) are to be understand as indirect evidence for a positive relation between inflation and risk aversion (uncertainty).

1.3.2.1 Non-Linearities

The paper by Bruno and Easterly (1998) shows that the effect of inflation on GDP growth only becomes negative once inflation is above a threshold level of 40 percent on an annual basis. This non-linear relation can be analyzed with more rigor since Hansen (2000, 1999) introduced panel threshold model estimation. In the studies that followed, the results show that below the threshold there is no significant relation between inflation and GDP growth rates, while above the threshold there is a robust negative relation [20].

In this paper, I am interested in testing if there is a significant threshold for the inflation - real earning growth relation. That is, if exists $\overline{\pi}$, such that when $\pi_t < \overline{\pi}$ the correlation is not significant. Following Hansen (2000), a threshold panel estimation is performed. For real earnings growth rates the model to estimate is

$$\triangle re_{it} = \alpha_i + \beta_1' \pi_{it} I(\pi_{it} \leq \overline{\pi}) + \beta_2' \pi_{it} I(\pi_{it} > \overline{\pi}) + \beta_3' \triangle GDP_{i,t-1} + \varepsilon_{it}$$

[20] A number of papers have analyzed the relation between inflation and GDP growth using threshold models. Drukker et al. (2005) use a non-dynamic, fixed effects panel data framework to analyze the correlation for 138 countries in the period 1950-2000. For the full sample, they find a threshold inflation level of 19.2 percent. Below this level, there is no significant effect of inflation on growth. Above the threshold, inflation correlates negatively with GDP growth rates. Khan and Senhadji (2001) find similar results, but for a balanced panel. For industrialized countries the threshold is between 0.89-1.11 percent inflation level, while for non-industrialized 10.62-11.38 percent. Using a dynamic panel approach, Kremer et al (2009) find a 2 percent threshold for industrialized and 17 percent threshold for non-industrialized.

where $\triangle re_{it}$ is the capital weighted real earning growth rate of market i and month t ; π_{it} is monthly inflation rate; $\triangle GDP$ is the real GDP growth rate, and $\overline{\pi}$ is the threshold inflation rate to be estimated.

Following the steps described in Appendix 1.1, I first find the threshold point estimation, which is 0.007452 (9.32 % annualized rate). Second, the model estimation is repeated, but differentiating with a dummy variable the effect of inflation being below or above the estimated threshold. The results are in Table 1.11. Column (i) shows the results when no threshold is assumed. Column (ii) shows the results for the estimation incorporating the threshold inflation rate. For that, two dummies are included in the specification, one having value 1 when $\pi_t < \overline{\pi}$ and 0 otherwise, and the other having value 1 when $\pi_t > \overline{\pi}$ and 0 otherwise. Note that when inflation is below or above the estimated threshold does not change the main results in the paper: either below or above the threshold, higher inflation correlates with lower real earnings growth rates. The conclusion from the threshold panel analysis is that inflation does correlate negatively with real earnings growth rates, independently of the inflation level. Thus, the results in previous sections do not suffer from any of the biases emphasized by the threshold-panel literature[21].

1.3.2.2 Quantifying the impact of decreasing real earnings growth rates on real stock price variations

Quantifying the impact of inflation on real earning growth rates allows explaining the actual variation in real stock prices when facing an inflation shock. Specifically, I estimate the share of the real stock price variation explained by inflation only affecting real earning growth rates. A simple way to estimate the share of the real stock price variation that is explained by inflation only affecting real earn-

[21] It's worth to emphasize that I am working with a special type of firm, since the average firm traded in the stock market is different from the average firm in the economy when working with EMs.

ings growth rates is to multiply the estimated coefficients coming from: i) regressing real stock prices on real earnings growth rates; and ii) regressing real earnings growth rates on inflation. The results from different specifications show that estimated share is between 18 and 20 percent. In other words, inflation only decreasing real earnings growth rates explains a fifth of the variation of the real stock price. Similar results are found when calibrating asset-pricing models to the EM sample.

The question then is what factors may explain the 80 percent of the real stock price variation that is not explained by decreasing real earnings growth rates. Bekaert and Engstrom (2010) find that, in the case of the US, the positive relation between inflation and risk explains almost half of the variation of the real stock price when fronting an inflation shock. Assuming this figure as a floor for EMs, then the room left unexplained is reduced to less than 30 percent. This implies that the room for money illusion in EMs is substantially less than in the case of developed markets. This seems puzzling, since developed markets are deeper, more liquid and transaction costs are lower than in EMs. In this case, non-arbitrage conditions seem more sensible in developed markets than in EMs, preventing recurrent valuation errors to exist. On the other side, it can be argued that the cost of inflation related valuation errors may be higher in EMs than in developed markets, which may explain the more extended presence of money illusion in developed countries.

1.4 SECTOR ANALYSIS

Two empirical questions can be answered when working with sector-portfolios: a) which sectors perform better as inflation hedges; and b) which sectors present higher earning resilience to inflation. In the case of EMs, I find that some sectors showing strong earnings resilience to inflation are nonetheless punished by the market as their real stock prices fall; while some sectors showing strong earning decreases are nonetheless good hedges against inflation, as their real stock prices do not fall and in some cases they even increase.

In Table 1.12, I present the future 12-month real earning growth rate variations and the monthly earning yield variation conditional on a five percent annualized inflation shock, for the most aggregated sector classification (10-sector aggregation). The only sector experiencing a 12-month increase in real earnings growth rates is Telecommunications. As expected, the earnings price variation presents a negative value implying an increase in the sector real stock price. The rest of the sectors present negative real earning variations and lower real stock prices (positive earning yield variation), with the notable exception of Utilities. For Utilities, stock prices increase even though earnings growth rates decrease. Therefore, in EMs, an index following Utilities seems to be the best stock market hedge against inflation.

In Figure 1.2, the variation in the future 12-month earning growth rate and the variation in the earning yield is plotted for the 60 sectors available at the lowest aggregation level. Again, a positive variation in the earning yield indicates a decrease in stock price. As expected, most of the sectors experience both a decrease in stock prices and real earnings due to inflation (sectors included in the quadrant IV). Telecommunication sub-sectors are the ones plotted in quadrant II (increasing earnings and real stock price). The sectors included in quadrant III present increasing stock prices and decreasing real earnings. The second part of Table 1.12 shows those sectors with increasing stock prices and decreasing real earnings. As expected, most of these are subsectors of Utilities. Note that Water Utilities and Wireless Communication Services have their stock prices increasing eventhough inflation severely punishes their earning growth rates.

Also puzzling is the presence of some sectors with positive earning growth rates and increasing stock prices (quadrant I). The problem is that most of these sectors are very small, with capitalization lower than one percent of the market. In order to control for very small sectors driving the results, in the second panel I only include sectors with capitalization higher than one percent. In this case, only two sectors present both an increase in prices and earnings: Marine and Multi-Utilities. Again, the capitalization of these two sectors is barely above the one percent threshold (1.4 and 1.1 percent), so other issues may be playing a big role in the correlations.

1.4.1 Sector-Portfolio Specification

In this section, I go through the results when working with the sector-portfolio specification. While the main results still apply, there is a new dimension to discuss in relation to the leverage channel. I find that the leverage channel is robust for big sectors, but not for small sectors. I conjecture that small sectors suffer more financial constraints than big ones, and therefore the effect for small sectors is not found to be significant.

The benchmark regression when working with sector-portfolios is

$$\frac{E}{P}_{kjt} = \alpha_0 + \alpha_1 \pi_{jt} + \alpha_2 \triangle gdp_{j,t+1} + \alpha_3 \pi_{jt}\, debt_{kjt} +$$

$$\dots + \alpha_4\, debt_{kjt} + \mu^k + \zeta^j + e_{kjt}$$

$$t = 1, \dots, T, \quad k = 1, \dots, K \quad j = 1, \dots, J$$

where the dependent variable $\frac{E}{P}_{kjt}$ is the earnings yield corresponding to sector k of market j at time t, π_{jt} is the month on month inflation rate of country j at time t; $gdp_{j,t+1}$ in next quarter actual GDP growth rate; $debt_{kjt}$ accounts for the market debt to capital ratio for sector k of country j at time t, and $\pi_{jt}\, debt_{kjt}$ is the interaction term between inflation and leverage. Fixed effects at a sector and market level are included when noted. A long panel estimation is performed, since the number of time periods is higher than the number of cross-section units. The results are reported in Table 1.13, which is divided in three panels. Panel A shows the benchmark specification adding a trend variable to control for common time effects. The estimated inflation coefficient is positive and highly significant, as expected. In Panel B, I control for the Fama proxy hypothesis by including next quarter real GDP growth rate. At a sector level, positive variations in next quarter GDP are associated with higher stock prices. The inflation coefficient remains positive and significant, when including next quarter GDP growth rate.

Finally, in Panel C, the leverage channel is tested. When including in the panel estimation the sector leverage variables, the estimated coefficients for inflation and next quarter economic growth rate do not show differences with the previous results, but the coefficient for the cross term of inflation and leverage presents a puzzling positive sign. This implies that the higher the firm leverage, the more the stock price decreases when inflation jumps. This result seems puzzling, in particular when we find a strong and robust positive effect when dealing with individual stocks and market earning yields. The main difference is that we are imposing an equal weight on each sector in the sector-portfolio panel estimation. That is, a small sector in Argentina weights the same as a big sector in the same country. When working with market earning yields this is not a problem, since capital weights are used to construct the dependent variable.

In order to test if big and small sector asymmetries are behind the results, the following specification is estimated

$$\frac{E}{P}_{kjt} = \alpha_0 + \alpha_1 \pi_{jt} + \alpha_2 \triangle gdp_{j,t+1} + \alpha_3 \pi_{jt} debt_{kjt} + \quad \ldots$$

$$\ldots \quad + \quad \alpha_4 \pi_{jt} debt_{kjt} \left(Cap_{kjt} - \overline{Cap}_{jt} \right) + e_{kjt}$$

$$t = 1, ..., T, \quad k = 1, ..., K \quad j = 1, ..., J$$

where the dependent variable $\frac{E}{P}_{kjt}$ is the earnings yield corresponding to sector k of country j at time t (weighted by firm capitalization). π_{jt} is the month on month inflation rate of country j at time t; $gdp_{j,t+1}$ in next quarter actual GDP growth rate; $\pi_{jt}debt_{kjt}$ is the cross-product of inflation times the sector leverage; and $(Cap_{kjt} - \overline{Cap}_{jt})$ is a weighting term denoting sector k capitalization minus the average sector capitalization of country j at time t. Fixed effects at a sector and country level are included when noted.

Including the sector weight $(Cap_{kjt} - \overline{Cap}_{jt})$ allows separating the leverage effect for big sectors (sectors which capitalization is above average) and small sectors (sectors which capitalization is below average). The results presented in Table 1.14 show that sector asymmetries are significant. When introducing sector country dummies -columns (iv) and (v)- the coefficient for the term $\pi_{jt}debt_{kjt}\left(Cap_{kjt} - \overline{Cap}_{jt}\right)$ becomes negative and significant. Moreover, the estimated coefficient for the term $\pi_{jt}debt_j$ is negative but not significant. From the model specification, the leverage effect can be decomposed as:

$$\frac{\partial^2 \frac{E}{P}}{\partial \pi \partial debt} = \alpha_3 + \alpha_4 \left(Cap_{kjt} - \overline{Cap}_{jt}\right) \tag{1.1}$$

Note that you can read the first term -α_3− as the coefficient for the average sector, being the average sector the one with capitalization equal to the average of all the sectors $(Cap_{kjt} = \overline{Cap}_{jt})$. Therefore, for the average sector the leverage impact is not significant. However, for big sectors the leverage channel is significant. The same is not true for small sectors (those below the average sector capitalization). In Figure 1.3, I plot the estimated impact of a one percent inflation rate on the earnings price, conditional on the capital weight of the sector as in Equation 1.1. For a sector above average, the effect is negative and significant, implying an increasing stock price for firms with higher leverage. On the other side, for sectors close to the average or below the average, the leverage effect is positive and non significant.

Under the sector-portfolio approach, I conclude that the leverage channel is present: higher inflation increases stock price conditional on firm leverage. However, the result does not hold for all the sectors, but for the big sectors. These are the ones that show a positive correlation of inflation on stock prices conditional on indebtedness. I conjecture that small sectors suffer more financial constraints than big ones, and therefore the effect for small sectors is not found to be significant. While there is a empirical evidence supporting this claim for developed markets, there is not evidence for EMs as an asset class. I leave testing this conjecture for future research.

1.5 Discussion and Conclusions

In this paper I provide new insights into the effects of inflation on real stock prices. Since the seminal work of Modigliani and Cohn (1979), the majority of papers have emphasized behavioral factors. I test the different real channels suggested in the literature in the case of EMs, and find strong empirical support for all of them. The results support Friedman's claim that inflation imposes real economic costs, and at the same time questions the need to build on money illusion and related approaches.

There are two real channels through which inflation imposes real costs on the economy. First, I find a negative and strong relation between inflation and real earning variations. The effect is large: an annualized 5 percent inflation rate decreases annual earning growth rates to 7.1 percent from the 8.4 percent unconditional mean, or, in other words, by 15 percent relative to the trend earning growth rate. The average inflation spell lasts twelve months. Moreover, using Hansen's (2000) panel threshold model estimation, there is no evidence of non-linearities in the inflation-earning growth rate relation. The results are robust to aggregation methods and data frequencies.

Second, there is a positive relation between inflation, risk aversion and uncertainty, as suggested by Bekaert and Engstrom (2010a). This channel is tested in an indirect way. First, I show that the relevant share of the explained variance driving the inflation-stock price correlation takes place in contraction periods. Since risk aversion and uncertainty are higher during recessions, these results can be taken as indirect evidence of the positive relation between inflation and risk aversion (uncertainty). Second, I show that the relation between inflation and real earnings growth rates does not show significant asymmetries conditioning on crisis-types: currency, banking and twin-crisis. However, the earning yield does show asymmetric responses conditioning on the type of crisis. As before, I interpret these results as inflation affecting risk quantity and risk price.

Under imperfect capital markets inflation may affect real stock prices in a positive way. As suggested by Ritter and Warr (2002), inflation affects equity values by decreasing the real value of corporate debt. For a given expected real cash flow (i.e. firm value), inflation decreases the real value of debt, increasing the equity value and thus driving stock prices upwards. The results show that this real channel, the leverage channel, plays a significant role in EMs. Higher inflation increases stock prices conditional on sector indebtedness. At a sector level, the evidence shows that the more indebted the sector, the higher the impact of inflation on the equity price, but the effect is not significant for small sectors. This is consistent with firms in small sectors suffering more from financial constraints than firms in big sectors.

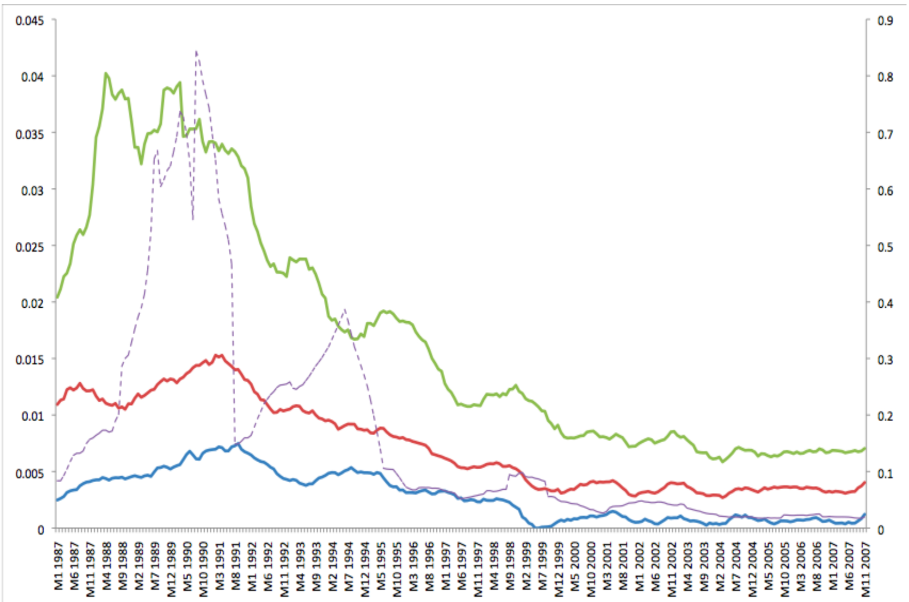
In order to gain further insights into the mechanisms driving the relation between inflation and real stock prices, I explore which sectors are the best hedges against inflation, and which sectors present highest earning resilience to inflation. Interestingly, the results show that some sectors present strong earning resilience to inflation but are nonetheless punished by the market, while some sectors that show strong earning decreases are good hedges against inflation. The factors explaining these sector asymmetries are left for future investigation.

The evidence for real channels in the EM sample allows discussing the room for money illusion when explaining the negative correlation between inflation and real stock prices. Inflation decreasing real earnings growth rates accounts for 20 percent if the real stock price variation. While in this paper I do not quantify the importance of the other two real channels, we can draw upon the literature for the risk channel. Bekaert and Engstrom (2010) show that, for the US, the inflation-risk relation explains up to 50 percent of the real stock price variation. Therefore, there is less room for money illusion in EMs than in developed markets, what seems to be a puzzling result.

Future research should seek to explain why inflation affects earnings, e.g. by increasing costs, by increasing tax distortions, or via decreased mark-ups. Also, it would be important to understand why these effects overcome the demand effects emphasized by monetary theories. Another key empirical challenge is to develop direct tests for the correlation between inflation and uncertainty, and inflation and risk aversion. Quantifying the risk-inflation relation is key to determine if there is room for money illusion, as discussed above.

Figure 1.1: Emerging Market Monthly Inflation Average

Notes: The figure shows average month on month inflation rates (seasonally adjusted). The 1st (in blue), 2nd (in red) and 3rd (in green) quartiles are plotted on the left axis. The 4th quartile (dotted line) is on the right axis. During the 80s, inflation monthly inflation was high and volatile (Great Inflation). After mid-90s, inflation decreased considerably and has remained low and stable since then.



Emerging Market Monthly Inflation Average

monthy figures (annualized figures in parentheses)

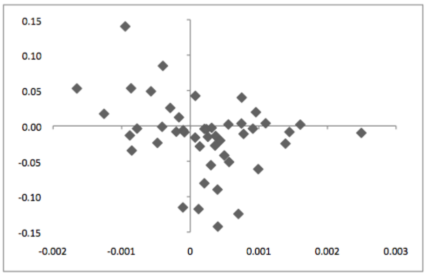
	1985-2007	1985-1990	1990-2000	2001-2007
Mean	0.01977 (0.2684)	0.05633 (0.9302)	0.017959 (0.2381)	0.00509 (0.0628)
Volatility	0.06576 (0.2278)	0.13887 (0.4811)	0.04555 (0.1578)	0.00686 (0.0237)
Skewness	12.02	8.19	5.43	4.83
Kurtosis	236.9	96.56	36.23	42.75

Figure 1.2: Earning Yield Variation and 12-Month Real Earning Growth Rate Variation

Notes: The figures show the estimated variation of earnings yield (monthly variation) and real earnings growth rates (12-month variation) given a 5 percent inflation shock. The horizontal axis plots the earning yield change, while the vertical axis the change in real earnings growth rates. Note that positive variations in earning yields imply a decrease in the stock price. Sectors with positive earnings growth rates and increasing stock prices are plotted in quadrant I; sectors with increasing earnings and real stock price in quadrant II; sectors with increasing stock prices and decreasing real earnings in quadrant III; and sectors with negative real earnings and decreasing stock prices in quadrant IV. The upper panel shows 60 sectors, while the lower panel shows only those sectors which capitalization is above one percent of the market capital.

60-Sector Aggregation

(earnings yield variation is plotted on horizontal axis while change in real earnings growth rates on vertical axis)



60-Sector Aggregation: Capitalization higher than one percent

(earnings yield variation is plotted on horizontal axis while change in real earnings growth rates on vertical axis)

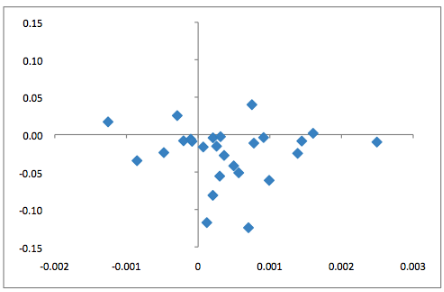


Figure 1.3: Leverage Effect and Sector Capitalization

Notes: The figure plots the leverage effect of inflation over earning yield, as described below. The horizontal axis shows the sector capital weights $\left(Cap_{kjt} - \overline{Cap}_{jt}\right)$. A positive effect implies a decrease in the stock price, while a negative figure implies an increase in the stock price. In the figure I plot the estimated impact of a one bps inflation rate on the earnings price, conditional on the leverage. Following the model in Eq (9), the leverage effect is: $\frac{\partial^2 \frac{e}{p}_{kjt}}{\partial \pi \partial Debt} = \alpha_3 + \alpha_4 \left(Cap_{kjt} - \overline{Cap}_{jt}\right)$. Note that you can read the first term -α_3− as the coefficient for the average sector, being the average sector the one with capitalization equal to the average of all the sectors $\left(Cap_{kjt} = \overline{Cap}_{jt}\right)$. The figure is done using the estimation in Table 4.2, column (v). For a sector above the average, the effect is negative and significant, implying an increasing stock price for firms with higher leverage. On the other side, for sectors close to the average or below the average, the leverage effect is positive and non significant.

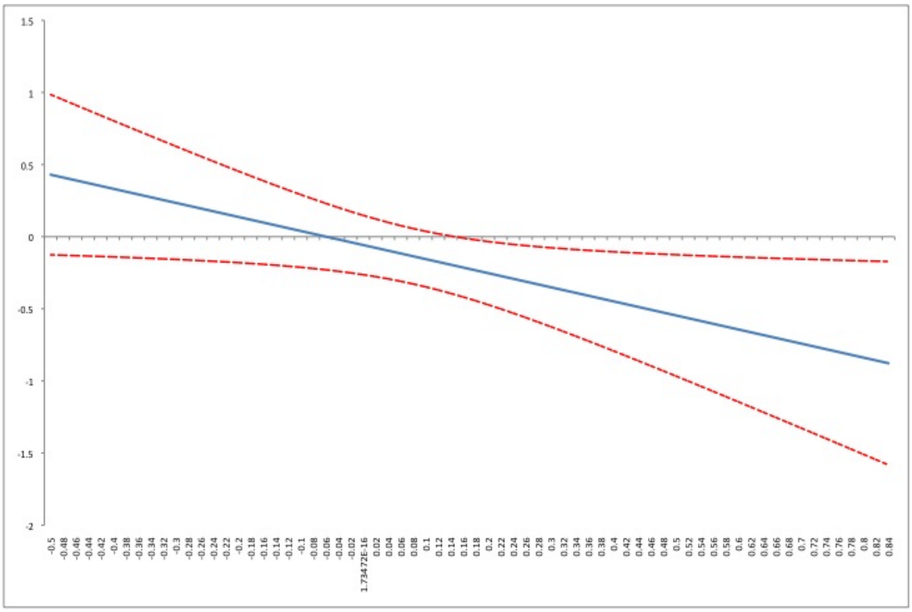


Table 1.1: Emerging Market Capitalization

Notes: the figures correspond to the sample average. Nominal exchange rates were used to translate capital from domestic currency into dollar denominated. The share is calculated over the 24 countries included in the EMDB database, of which due to data issues I end up working with 15 countries.

Country	Share
Korea	13.9%
Brazil	9.2%
India	9.1%
Malaysia	5.5%
Mexico	5.3%
Chile	2.7%
Turkey	2.5%
Poland	1.9%
Argentina	0.9%
Peru	0.8%
Egypt	0.8%
Czech Republic	0.7%
Hungary	0.7%
Colombia	0.4%
Venezuela	0.2%

Table 1.2: Sector Capitalization

Notes: the figures correspond to the sample average. Nominal exchange rates were used to translate capital from domestic currency into dollar denominated.

Sector	Share
Telecom	15.40%
Banks	15.00%
Materials	12.60%
Energy	8.30%
Utilities	8.20%
Food, Beverage and Tobacco	6.80%
Capital Goods	6.30%
Pharmaceuticals	4.10%
Software, Tech Hardware	2.80%
Auto	2.40%
Diverse Financials	2.40%
Retailing	2.20%
Consumer Durables	2.00%
Real Estate	2.00%
Food & Drug Retail	1.90%
Transportation	1.60%
Media	1.30%
Commercial Services	1.30%
Household Products	1.30%
Insurance	1.10%
Hotels & Restaurants	0.80%
Heath Equipment	0.30%

Table 1.3: Country-Sector Leverage

Notes: The leverage ratios are obtained from Bloomberg for the years 2006-2007. The ratios correspond to market debt to capital ratios. In the table I present the leverage figures at highest sector aggregation (10-sector aggregation).

	Energy	**Materials**	**Industrials**	**Consumer Discret.**	**Consumer Staples**	**Health Care**	**Financials**	**Information Tech**	**Telecos**	**Utilities**	**Mean**
Czech Rep	0.22	0.58	na	0.02	0.60	0.10	0.25	0.20	0.05	0.10	**0.13**
Hungary	0.08	0.23	0.15	0.15	na	na	0.28	na	0.25	0.12	**0.18**
Poland	0.16	0.10	0.06	0.11	0.16	0.06	0.16	0.06	0.11	0.32	**0.13**
Turkey	0.09	0.12	0.25	0.17	0.15	0.09	0.38	0.01	0.03	0.32	**0.16**
Argentina	0.02	0.15	na	0.09	0.09	na	0.47	na	0.25	0.52	**0.22**
Brazil	0.41	0.33	0.48	0.19	0.22	0.06	0.26	0.01	0.26	0.68	**0.29**
Chile	na	0.13	0.21	0.12	0.17	0.05	0.27	0.25	0.24	0.48	**0.21**
Colombia	na	0.36	0.18	na	0.10	na	0.24	na	0.56	0.37	**0.30**
Mexico	na	0.18	0.23	0.4	0.27	0.02	0.13	na	0.32	na	**0.22**
Peru	0.09	0.13	0.33	0.52	0.25	na	0.16	na	0.15	0.36	**0.25**
Venezuela	na	0.05	0.01	na	na	na	0.24	na	0.03	0.33	**0.13**
Egypt	na	0.11	0.12	0.15	0.09	0.12	0.16	na	0.10	na	**0.12**
India	0.11	0.18	0.10	0.18	0.18	0.12	0.24	0.06	0.12	0.13	**0.14**
Korea	0.21	0.29	0.22	0.21	0.25	0.11	0.36	0.14	0.13	0.44	**0.24**
Malaysia	0.20	0.22	0.26	0.18	0.14	0.19	0.31	0.10	0.08	0.64	**0.23**
Mean	**0.14**	**0.28**	**0.22**	**0.21**	**0.18**	**0.10**	**0.29**	**0.10**	**0.21**	**0.36**	**0.23**

Table 1.4: Inflation and Real Stock Prices: Stock Specification

This table reports a panel estimation to test the effect of monthly inflation on real stock prices. The dependent variable is the monthly earnings price ratio for each stock traded in the Emerging Market sample. Independent variables are: INF is the monthly inflation rate; GDP is the next quarter actual GDP growth rate, as a proxy for expected growth. DEBT is a variable that controls leverage, the debt to capital ratio (mark to market), from Bloomberg. See Section 2 for construction of the leverage series. INF*DEBT is the cross-product of INF and DEBT variables. The table reports point estimates with t-statistics (in parentheses) clustered as described in the Cluster row. Country dummy variables, and fixed effects added when noted. ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

PANEL A

	Dependent Variable: $\frac{E}{P}_{ijt}$			
	(i)	(ii)	(iii)	(iv)
INF(-1)	0.2770***	0.2770***	0.2158	0.2158***
	(3.3806)	(2.9252)	(1.6211)	(3.4570)
GDP			0.0984	0.0984
			(0.4446)	(0.1927)
Fixed Effects	Yes	Yes	Yes	Yes
Cluster	-	Market	-	Market
Observations	126303	126303	69966	69966
Number of Markets	15	15	15	15

PANEL B

	Dependent Variable: $\frac{E}{P}_{jt}$				
	(i)	(ii)	(iii)	(iv)	(v)
INF(-1)	1.1305***	1.3447*	1.3447***	1.4956***	1.8744**
	(4.3333)	(1.7413)	(3.3257)	(3.2667)	(3.0039)
GDP	0.0975	0.0250	0.0250	0.0051	-0.5392
	(0.3852)	(0.0450)	(0.0354)	(0.0076)	(-1.7233)
INF*DEBT (-1)	-2.8618***	-3.1513*	-3.1513***	-4.3639***	-5.7301**
	(-4.6310)	(-1.9215)	(-3.0281)	(-3.4442)	(-2.9049)
INF*REC (-1)				0.3440*	1.4795
				(1.8442)	(1.3156)
GDP*REC					3.7255
					(0.7408)
INF*DEBT*REC (-1)					-3.6497
					(-1.2516)
DEBT (-1)	-0.1276	-	-	-	-
	(-1.0276)	.	.	.	.
REC (-1)				-0.0126	-0.0056
				(-0.6459)	(-0.3926)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	-	-	Market	Market	Market
Observations	60652	60652	60652	60090	59984
Number of Markets	15	15	15	15	15

Table 1.5: Inflation and Real Stock Prices: A Market-Portfolio Specification

This table reports a long panel estimation test the effect of monthly inflation on real stock prices. The dependent variable is the monthly earnings price ratio for each Emerging Market included in the sample. Independent variables are: INF is the monthly inflation rate; GDP is the next quarter actual GDP growth rate, as a proxy for expected growth. DEBT is the market debt to capitalization ratio, capital weighted. REC is a dummy variable taking value one if GDP variation is negative (contraction) and zero if positive (expansion). The long panel estimation controls for autocorrelation, cross-correlation, and heterokesdacitiy in the panels. For each panel, an idiosincratic autocorrelation parameter is estimated under the assumption that errors for each portfolio follow an autoregressive process of order one. The table reports point estimates with t-statistics (in parentheses). Country dummy variables, and other controls added when noted. ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

	Dependent Variable: $\frac{E}{P}_{jt}$			
	(i)	(ii)	(iii)	(iv)
INF (-1)	0.3786***	-0.0212	0.2896*	0.2485
	(2.6165)	(-0.2873)	(1.8922)	(1.6096)
INF*REC (-1)		0.2033**	0.1728*	0.6448***
		(2.1180)	(1.8084)	(2.5813)
INF*DEBT (-1)	-1.6983***		-1.5032**	-1.4028**
	(-2.7775)		(-2.4188)	(-2.2522)
INF*DEBT*REC (-1)				-2.3816**
				(-2.0457)
GDP	0.0674	0.0607	0.0509	0.0515
	(1.1222)	(0.8731)	(0.7443)	(0.7534)
DEBT	-0.4732***		-0.4270***	-0.4248***
	(-3.2750)		(-2.7847)	(-2.7794)
REC (-1)		0.0074**	0.0074**	0.0072**
		(2.0384)	(2.0574)	(2.0247)
Country Dummy	Yes	Yes	Yes	Yes
Observations	2575	2575	2575	2575
Number of Markets	15	15	15	15

Table 1.6: Real Stock Prices, Inflation and Inflation Volatility

This table reports a long panel estimation to test the effect of monthly inflation on real stock prices. The dependent variable is the monthly earnings price ratio each Emerging Market in the sample. Independent variables are: INF is the monthly inflation rate; GDP is the next quarter actual GDP growth rate, as a proxy for expected growth. DEBT is the market debt to capitalization ratio, capital weighted. The variable VOLATILITY corresponds to the estimated conditional variance for the monthly inflation rate coming from a GARCH process. The long panel estimation controls for autocorrelation, cross-correlation, and heterokesdacitiy in the panels. For each panel, an idiosincratic autocorrelation parameter is estimated under the assumption that errors for each portfolio follow an autoregressive process of order one. The table reports point estimates with t-statistics (in parentheses). Country dummy variables and other controls added when noted. ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

	Dependent Variable: $\frac{E}{P}_{jt}$			
	(i)	(ii)	(iii)	(iv)
INF (-1)	0.0325	0.0748	0.2800**	0.2807*
	(0.6051)	(1.1061)	(1.9720)	(1.9422)
VOLATILITY (-1)	-0.0542	0.0333	0.0998	0.0901
	(-0.3487)	(0.1288)	(0.3754)	(0.1820)
GDP		0.0782	0.0683	0.0684
		(1.3333)	(1.1674)	(1.1686)
INF*DEBT (-1)			-1.0346*	-1.0434*
			(-1.7113)	(-1.7064)
DEBT (-1)			-0.4318***	-0.4333***
			(-2.9881)	(-2.9993)
VOLATILITY*DEBT (-1)				0.0569
				(0.0228)
Country Dummy	Yes	Yes	Yes	Yes
Observations	3222	2638	2638	2638
Number of Markets	15	15	15	15

Table 1.7: Inflation and Real Stock Prices: Crisis Typology

This table reports a long panel estimation to test the effect of monthly inflation on real stock prices. The dependent variable is the monthly earnings price ratio. Independent variables are: INF is the monthly inflation rate; GDP is the next quarter actual GDP growth rate, as a proxy for expected growth. The variables Crisis_Curren, Crisis_Bank and Crisis_Twin are dummy variables taking value one when the period corresponds to a currency, banking or twin crisis months, as described in Section 2. The variables INF*CURR, INF*BANK and INF*TWIN correspond to the cross product of inflation and each of the dummy variables described before. The variables INF*DEBT*CURR, INF*DEBT*BANK and INF*DEBT*TWIN correspond to the cross product of inflation, leverage and each of the dummy variables described before. The long panel estimation controls for autocorrelation, cross-correlation, and heterokesdacitiy in the panels. For each panel, an idiosincratic autocorrelation parameter is estimated (assumption is that errors for each portfolio follow an autoregressive process of order one. The table reports point estimates with t-statistics (in parentheses) clustered as described in the Cluster row. Country dummy variables, and fixed effects added when noted. . ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

	Dependent Variable: $\frac{E}{P}_{jt}$				
	(i) All Periods	(ii) Currency Crisis	(iii) Banking Crisis	(iv) Twin Crisis	(v) Non-Twin Crisis
INF (-1)	0.5034**	0.4322*	0.5708**	0.4780**	0.4801*
	(2.1756)	(1.7116)	(2.4499)	(1.9810)	(1.9353)
INF*CURR (-1)		8.2896***			12.7159***
	(3.0051)			(3.9370)	
INF*BANK (-1)			0.8508		2.0350
			(0.5624)		(1.0248)
INF*TWIN (-1)				-1.4077	
				(-0.4564)	
INF*DEBT (-1)	-2.2543**	-1.8984*	-2.6842***	-2.1233**	-2.4290**
	(-2.3580)	(-1.8896)	(-2.8031)	(-2.1786)	(-2.4392)
INF*DEBT*CURR (-1)		-48.5848***			-75.2669***
		(-3.4305)			(-4.5373)
INF*DEBT*BANK (-1)			-0.7977		-4.0580
			(-0.1916)		(-0.7489)
INF*DEBT*TWIN (-1)				5.3047	
				(0.3309)	
DEBT	-0.0891	-0.1110	-0.0698	-0.0764	-0.1687
	(-0.6213)	(-0.7456)	(-0.4869)	(-0.5366)	(-1.1347)
GDP (+1)	-0.0765	-0.0537	-0.0655	-0.0676	-0.0331
	(-1.3758)	(-0.8878)	(-1.1646)	(-1.1846)	(-0.5447)
Currency_crisis		0.0371**			0.0179
		(2.5213)			(1.0051)
Banking_crisis			0.0055		-0.0306*
			(0.3666)		(-1.7566)
Twin_crisis				0.0508**	
				(1.9832)	
Observations	2357	2357	2357	2357	2326
Country Dummy	Yes	Yes	Yes	Yes	Yes
Number of Markets	15	15	15	15	15

Table 1.8: Real Earnings and Inflation

A. Stock Specification

This table reports a panel estimation to test the effect of monthly inflation on real earnings growth rates. The dependent variable is the monthly real earnings variation for each stock traded in fifteen emerging markets. Independent variables are: INF is the monthly inflation rate; GDP is the previous quarter actual GDP growth rate. The table reports point estimates with t-statistics (in parentheses), clustered as described in the Cluster row. Country dummy variables, and fixed effects added when noted. ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

	Dependent Variable: Real earnings growth rates			
	(i)	(ii)	(iii)	(iv)
INF (-1)	-0.1799***	-0.2333**	-0.2426***	-0.2426***
	(-6.0320)	(-3.0115)	(-3.3410)	(-3.3410)
GDP (-1)		0.1625	0.1865	0.1865
		(1.6408)	(1.3652)	(1.3652)
Month Dummy	No	No	Yes	Yes
Country Dummy	No	No	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Cluster	Market	Market	Market	Market
Observations	111041	94485	94485	94485
Number of Markets	15	15	15	15

Cont.

Table 1.8(Cont.): Real Earnings and Inflation

B. Market-Portfolio Specification

This table reports a long panel estimation to test the effect of monthly inflation on real earnings growth rates. The dependent variable is the monthly real earnings variation for fifteen emerging countries. Independent variables are: INF is the monthly inflation rate; GDP is the j -previous quarter GDP growth rate. The long panel estimation controls for autocorrelation, cross-correlation, and heterokesdacitiy in the panels. For each panel, an idiosincratic autocorrelation parameter is estimated, assuming that errors for each portfolio follow an autoregressive process of order one. The table reports point estimates with t-statistics (in parentheses). Country dummy variables are added when noted. A TREND variable is added. ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

	Dependent Variable: Real Earnings Growth Rates					
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
INF t	-0.3972***					
	(-4.0722)					
INF t-1		-0.3546***				
		(-3.5128)				
INF t-2			-0.1759			
			(-1.6102)			
GDP q-1	0.1734**	0.1485**	0.1533**			
	(2.2959)	(1.9821)	(2.0213)			
INF t-3				-0.2345**		
				(-2.2548)		
INF t-6					-0.2017**	
					(-2.2015)	
GDP q-2				0.1545**	0.1744**	
				(2.0213)	(2.3096)	
INF t-9						-0.2826***
						(-2.8126)
GDP q-3						0.2459***
						(3.2043)
TREND	0.0001**	0.0001**	0.0001**	0.0001***	0.0001***	0.0001***
	(2.3368)	(2.2164)	(2.2478)	(2.9499)	(3.0878)	(3.1689)
Country Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3233	3146	3148	3080	3173	3121
Number of Markets	15	15	15	15	15	15

Table 1.9: Real Earnings, Inflation and Economic Cycle

This table reports a long panel estimation to test the effect of monthly inflation on real earnings growth rates. The dependent variable is the monthly real earnings variation for fifteen emerging countries. Independent variables are: INF is the monthly inflation rate; GDP is the j -previous quarter GDP growth rate. REC is a dummy variable taking value one if GDP variation is negative (contraction) and zero if positive (expansion). The long panel estimation controls for autocorrelation, cross-correlation, and heterokesdacitiy in the panels. For each panel, an idiosincratic autocorrelation parameter is estimated, assuming that errors for each portfolio follow an autoregressive process of order one. The table reports point estimates with t-statistics (in parentheses). Country dummy variables are added when noted. ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

	Dependent Variable: Real earnings growth rates					
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
INF	-0.3623***					
	(-5.3785)					
INF*REC	0.0054					
	(0.0276)					
INF (-1)		-0.2394***				
		(-3.0100)				
INF*REC (-1)		0.1315				
		(0.5936)				
INF (-2)			-0.1757**			
			(-2.3987)			
INF*REC (-2)			0.0449			
			(0.2037)			
INF (-3)				-0.0578		
				(-0.7640)		
INF*REC (-3)				-0.0488		
				(-0.2262)		
INF (-6)					-0.2632***	
					(-3.8757)	
INF*REC (-6)					-0.2659	
					(-1.2066)	
INF (-9)						-0.1752**
						(-2.1764)
INF*REC (-9)						0.1724
						(0.7075)
REC	-0.0018					
	(-0.3744)					
REC (-1)		-0.0044				
		(-0.8982)				
REC (-2)			-0.0119**			
			(-2.4043)			
REC (-3)				-0.0052		
				(-1.0304)		
REC (-6)					-0.0082	
					(-1.5962)	
REC (-9)						-0.0161***
						(-3.0589)
Trend	0.00001**	0.00001*	0.00001**	0.0001**		0.00001*
	(1.9793)	(1.8771)	(2.1351)	(2.5028)		(1.8433)
Observations	4356	4207	4170	4148	4075	4013
Country Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Number of Markets	15	15	15	15	15	15

Table 1.10: Real Earnings and Inflation: Crisis Typology

This table reports a long panel estimation to test the effect of monthly inflation on real earnings growth rates. The dependent variable is the monthly real earning variation for fifteen emerging countries. Independent variables are: INF is the monthly inflation rate; GDP is the j-previous quarter GDP growth rate. The variables CURR, BANK and TWIN are dummy variables taking value one when the period corresponds to a currency, banking or twin crisis month. See Section 2 for the details on the series construction. The variables INF*CURR, INF*BANK and INF*TWIN correspond to the interaction term between inflation and each of the dummy variables described before. The long panel estimation controls for autocorrelation, cross-correlation, and heterokesdacitiy in the panels. For each panel, an idiosincratic autocorrelation parameter is estimated, assuming that errors for each portfolio follow an autoregressive process of order one. The table reports point estimates with t-statistics (in parentheses). Country dummy variables are added when noted. ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Curr-Crisis	-0.0250**			-0.0008	-0.0170*			0.0050				
	(-2.5347)			(-0.0595)	(-1.7440)			(0.3687)				
Bank-Crisis		-0.0173**		0.0004		-0.0174**		-0.0052				
		(-2.0923)		(0.0427)		(-2.1669)		(-0.5358)				
Twin-Crisis			-0.0559***				-0.0425***					
			(-3.8610)				(-3.0415)					
INF (-1)					-0.2520***	-0.2568***	-0.2537***	-0.2671***	-0.2625***	-0.2902***	-0.2527***	-0.3166***
					(-3.3549)	(-3.4346)	(-3.3955)	(-3.5541)	(-3.4604)	(-3.6277)	(-3.3796)	(-3.8709)
INF*CURR(-1)									0.2345			0.2822
									(0.8357)			(0.9593)
INF*BANK(-1)										0.2024		0.2191
										(1.1511)		(1.2433)
INF*TWIN(-1)											-0.0276	
											(-0.0393)	
Curr-Crisis(-1)									-0.0200*			0.0042
									(-1.9539)			(0.3001)
Bank-Crisis(-1)										-0.0175**		-0.0042
										(-2.1840)		(-0.4414)
Twin-Crisis(-1)											-0.0510***	
											(-3.0583)	
Observations	4356	4356	4356	4306	4207	4207	4207	4162	4207	4207	4207	4162
Country Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Markets	15	15	15	15	15	15	15	15	15	15	15	15

Table 1.11: Inflation and Real Earnings: Testing Non-linearities

This table reports a long panel estimation to test the effect of monthly inflation real earnings growth rates using a non-dynamic panel-data threshold approach. The dependent variable is real earnings growth rates. Independent variables are: INF is the previous month inflation rate; I() is a dummy variable taking value 0 if inflation ia below the estimated threshold and 1 otherwise; GDP is the following quarter GDP growth rate. DEBT corresponds to market leverage. The thresholds inflation was estimated in advance, by minimizing the estimated sum of squared errors for different threshold inflation levels. The estimated threshold level is 0.007452 (9.32 % annualized rate). The long panel estimation controls for autocorrelation, cross-correlation, and heterokesdacitiy in the panels. For each panel, an idiosincratic autocorrelation parameter is estimated, assuming that errors for each portfolio follow an autoregressive process of order one. The table reports point estimates with t-statistics (in parentheses). Country dummy variables are added when noted. ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

	Dependent Variable: Real earnings growth rates	
	(i) No Threshold	(ii) Threshold
INF	-0.4024***	
	(-4.2049)	
INF*I(0)		-0.6721***
		(-3.5871)
INF*I(1)		-0.3147***
		(-2.9946)
GDP	0.1203	
	(1.5230)	
GDP_d		0.1149
		(1.4564)
Trend	0.0001*	0.0000*
	(1.9023)	(1.7548)
Number of Observations	2480	2480

Table 1.12: Inflation Hedges at a Sector Level

i) 12-month Real Earning Variation and Earning Yield Variations

Sector	12-Month Real Earning Growth Rate	E/P Variation
Telecommunication Services	0.80%	-0.0024
Consumer Staples	-0.40%	0.0011
Energy	-0.70%	0.0010
Financials	-1.50%	0.0017
Utilities	-1.60%	-0.0011
Consumer Discretionary	-2.70%	0.0022
Materials	-3.00%	0.0009
Industrials	-3.00%	0.0008
Information Technology	-4.00%	0.0005
Aggregate	-1.30%	0.0189

ii) Sectors Showing Falling Earnings and Decreasing Earning Yields

Sector	12-Month Real Earning Growth Rate	E/P Variation
Water Utilities	-13.60%	-0.00386
Wireless Telecom. Services	-13.00%	-0.00451
Gas Utilities	-3.50%	-0.00085
Airlines	-2.40%	-0.00048
Textiles, Apparel & Luxury Goods	-1.30%	-0.00088
Beverages	-0.90%	-0.00009
Electric Utilities	-0.80%	-0.00020
Oil, Gas & Consumable Fuels	-0.60%	-0.00010
Air Freight & Logistics	-0.40%	-0.00078
Internet Software & Services	-0.10%	-0.00041

Table 1.13: Stock Prices and Inflation: A Sector-Portfolio Analysis

This table reports a long panel estimation to test the effect of monthly inflation on stock prices. The dependent variable is the monthly earnings price ratio for each of the 60 sectors corresponding to the countries included in the sample (see Section 2). Independent variables are: INF is the monthly inflation rate; GDP is the next quarter actual GDP growth rate, as a proxy for expected growth. DEBT is the leverage ratio (marketed to market), sector-capital weighted. REC is a dummy variable taking value one if GDP variation is negative (contraction) and zero if positive (expansion). The long panel estimation controls for autocorrelation, cross-correlation, and heterokesdacitiy in the panels. For each panel, an idiosincratic autocorrelation parameter is estimated under the assumption that errors for each portfolio follow an autoregressive process of order one. The table reports point estimates with t-statistics (in parentheses). Country and sector dummy variables added when noted. ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

	Dependent Variable: $\frac{E}{P}_{jt}$		
		PANEL A	
	(i)	(ii)	(iii)
INF	0.0476***	0.0494***	0.0449***
	(4.3569)	(4.4626)	(4.5855)
Trend		-0.0002***	-0.0002***
		(-4.4030)	(-6.0276)
Country Dummy	No	No	Yes
Sector Dummy	No	No	Yes
Observations	39767	39767	39767
		PANEL B	
	(i)	(ii)	(iii)
INF	0.0660***	0.0639***	0.0606***
	(4.7491)	(4.6039)	(4.9338)
GDP	-0.0339**	-0.0370***	-0.0495***
	(-2.3747)	(-2.5855)	(-3.5705)
Trend		-0.0002***	-0.0003***
		(-4.3049)	(-9.4477)
Country Dummy	No	No	Yes
Sector Dummy	No	No	Yes
Observations	21486	21486	21486
		PANEL C	
	(i)	(ii)	(iii)
INF	0.0758***	0.0614***	0.0601***
	(5.7380)	(4.6438)	(4.6792)
GDP	-0.0403***	-0.0418***	-0.0497***
	(-2.7776)	(-2.9272)	(-3.5716)
INF*DEBT	0.1743**	0.1230	0.1278*
	(2.2963)	(1.6318)	(1.8369)
DEBT	-0.0940***	-0.1048***	-0.1713***
	(-4.1620)	(-4.3383)	(-4.8028)
Trend		-0.0002***	-0.0003***
		(-7.1656)	(-9.6103)
Country Dummy	No	No	Yes
Sector Dummy	No	No	Yes
Observations	21414	21414	21414
Number of Markets	15	15	15

Table 1.14: Stock Prices and Inflation: Controlling for Sector Size Asymmetries

This table reports a long panel estimation to test the effect of monthly inflation on real stock prices. The dependent variable is the monthly earning-price ratio for each of the 60 sectors correpospond-ing to the countries included in the sample. Independent variables are: INF is the monthly inflation rate; GDP is the next quarter actual GDP growth rate, as a proxy for expected growth. DEBT is the leverage ratio (marketed to market), sector-capital weighted. REC is a dummy variable taking value one if GDP variation is negative (contraction) and zero if positive (expansion). The long panel estimation controls for autocorrelation, cross-correlation, and heterokesdacitiy in the panels. For each panel, an idiosincratic autocorrelation parameter is estimated under the assumption that errors for each portfolio follow an autoregressive process of order one. The table reports point estimates with t-statistics (in parentheses). Country dummy variables, and other controls added when noted. ***p<0.01, **p<0.05, *p<0.1. The sample period is January 1986-December 2007.

	Dependent Variable: $\frac{E}{P}_{jt}$				
	(i)	(ii)	(iii)	(iv)	(v)
INF (-1)	0.1000***	0.0930***	0.0855***	0.0861***	0.0893***
	(3.7295)	(3.4495)	(3.1524)	(3.2451)	(3.4102)
GDP	-0.0424***	-0.0460***	-0.0472***	-0.0508***	-0.0502***
	(-2.7667)	(-3.0286)	(-3.1533)	(-3.4244)	(-3.4540)
INF*DEBT(-1)	-0.0892	-0.0832	-0.0529	-0.0421	-0.0578
	(-0.6573)	(-0.6129)	(-0.3986)	(-0.3433)	(-0.4638)
INF*DEBT*Capital Weight(-1)	-0.8439	-0.8880	-0.7249	-0.8831*	-0.9754*
	(-1.0717)	(-1.1397)	(-1.0637)	(-1.6596)	(-1.7977)
DEBT*Capital Weight(-1)	0.0959	0.1210	0.1086	0.1303*	0.1520**
	(1.0546)	(1.3304)	(1.2198)	(1.7513)	(1.9621)
Capital Weight(-1)	-0.0163	-0.0257	-0.0253	-0.0411**	-0.0463**
	(-0.8834)	(-1.3670)	(-1.3143)	(-2.3913)	(-2.5692)
DEBT(-1)	-0.0506**	-0.0618***	-0.0527**	-0.1151***	-0.0862**
	(-2.2539)	(-2.6144)	(-2.3563)	(-3.8986)	(-2.5610)
Trend		-0.0002***	-0.0002***	-0.0002***	-0.0003***
		(-7.9076)	(-7.8837)	(-7.3556)	(-9.7345)
Constant	0.0550***	0.1257***	0.1555***	-0.0334	-0.0188
	(17.4041)	(11.9525)	(5.0587)	(-0.0963)	(-0.0000)
Country Dummy	No	No	Yes	No	Yes
Sector Dummy	No	No	No	Yes	Yes
Observations	21414	21414	21414	21414	21414
Number of Markets	15	15	15	15	15

2 EXPLAINING THE STOCK PRICE-INFLATION PUZZLE: INFLATION AS A SIGNAL FOR A STAGFLATION EVENT

2.1 INTRODUCTION

If stocks are a claim on real capital, the correlation between real stock prices and inflation should be null. However, the empirical findings show a robust negative correlation between inflation (realized, expected and unexpected) and real stock prices[1]. This is known as the stock price-inflation puzzle[2]. To illustrate the puzzle, in Figure 2.1, I plot the monthly stock yields and inflation rates (seasonally adjusted, month on month variations) for US 1970-2007. Given that dividends are very persistent, the positive slope can be translated into a negative correlation between inflation and real stock prices.

A closely related stream of the literature, known as the Fed Model, deals with the positive correlation between stock yields and nominal bond yields[3]. Since inflation and bond yields are highly correlated, the Fed Model is just a re-statement of the stock price-inflation puzzle. Bekaert and Engstrom (2009) show that the lion-share of the cor-

[1]For realized inflation see e.g. Fama and Schwert (1979); for expected inflation see e.g. Fama (1981); and for unexpected inflation see e.g. Amihud (1996).

[2]There are two main approaches attempting to explain the stock price-inflation puzzle: i) the friction approach; and ii) the behavioral approach. On the one side, the friction approach aims to explain how higher realized or expected inflation causes lower real cash flows in the future (see e.g. Joutz 2007; Wei 2007; Geske and Roll 1983, Danthine and Donaldson 1986). On the other side, the behavioral approach relies on money illusion: investors confuse nominal and real discount rates. Thus, given future real cash flows, higher inflation leads to higher discount rates (nominal interest rates), and therefore to lower stock prices (see Modigliani and Cohn 1979; Campbell and Vuolteenaho 2004; Apergis and Eleftheriou 2002, Cohen et al. 2005, ; Brunnermeier and Julliard 2006; Schmeling and Schrimpf 2008).

[3]See e.g. Asness (2002) and Bekaert and Engstrom (2009).

relation between stock and bond yields is explained by the correlation between risk and inflation. However, the authors don't present a theoretical framework to understand why both risk price and quantity increase with inflation. Brandt and Wang (2003) work a model in which time varying risk aversion depends on both news about consumption growth (as in a habit formation model) and news about inflation. The relation between inflation and risk aversion is an assumption of the model.

The main contribution of this paper is to suggest an explanation for the positive correlation between inflation and risk. In this framework, agents use realized inflation rates as a proxy for the probability of a rare event, namely high inflation accompanied by stalling or negative economic growth (stagflation)[4]. When agents observe increasing inflation rates, they perceive an increase in the probability of experiencing a stagflation episode in the future. Consequently, agents demand a higher premium, and stock prices decrease.

I present a simple model in which agents use realized inflation to update their beliefs on a time-dependent rare-event probability[5]. In the model, the monetary authority has a dual mandate on inflation and unemployment. In other words, the Fed loss function depends on the inflation rate and the output gap. In every period, the agents form expectations on the Fed commitment to low and stable inflation. If

[4]I thank Professor Bekaert for suggesting me to use stagflation as the bad state of nature.

[5]Models that try to explain stylized facts of asset prices incorporating learning and two states of the world are not new. Cecchetti et al. (2000) present a model in which agents have permanently distorted beliefs, never learning from experience that low-growth state occurs less than predicted ex-ante, and explain much of the equity premium. Veronesi (2004) shows that adding a learning process to a peso problem hypothesis can explain most if the stock markets' stylized facts. Cogley and Sargent (2008) analyze the case in which agents update their estimates of transition probabilities to a bad state (1930's Great Depression) according to Bayes' law. They include a negative prior (high probability of the bad state) at the beginning of the learning process in order to explain the equity premium. In this paper, the prior on the bad state probability depends on realized inflation and on the agents' expected low-inflation commitment of the monetary authority.

the agents expect a weak commitment to low inflation, the probability of stagflation in the future increases, and thus the effect of a one basis point increase in realized inflation on stock prices should be higher than in the case where agents expect a strong commitment to low inflation.

I perform Markov Switching Regime estimations to test the model. The regimes are aimed to control for agent's expectations on the Fed commitment. The results go in line with the model implications. First, when realized inflation increases real stock price decreases. Second, I find two significant states. Regime-1 is related to an expected weak Fed commitment to low inflation, while in Regime-2 agents expect the Fed to show a strong commitment to low inflation. The probability of Regime-1 is close to one until 1984, while the probability of the Regime-2 is close to one since 1991, except for the period 2000-2002 and for the 2008-2009 crisis period[6]. Third, the estimated effect of inflation on real stock prices is higher in Regime-1 than in 2, and statistically different in both regimes. An inflation increase of one basis point decreases stock prices in 16 bps in Regime-1 (7 bps in Regime-2). The results are robust to different measures of inflation: headline inflation, core inflation (headline inflation excluding food and energy prices), headline inflation excluding food prices, and headline inflation excluding energy prices.

The correlation of inflation with both uncertainty and risk aversion comes from the fact that during recessions, the estimated probability of Regime-1 jumps to be close to 1. Thus, when unemployment is high, the probability of the Fed weighting less on inflation and more on output gap increases. Thus, when the economy is in recession (high uncertainty and risk aversion), the probability of the rare event is higher than when the economy is in expansion (low uncer-

[6]This piece of evidence can be related to Bianchi (2009). He shows that the behavior of the FED has fluctuated between what he calls a Hawk regime (weighting more low inflation) and a Dove regime (weighting less low inflation).

tainty and risk aversion). Therefore, the correlation between inflation and real stock prices is stronger during recession periods.

An increase in inflation rates when the economy is in recession may also be understood as positive news. If demand is increasing more than supply, then higher prices may be signaling the end of the recession. To control for this effect, I include in the estimations expected variations in production. I use expected variations in GDP coming from surveys, both the Livingstone survey and Professional Forecaster survey. I also control for recessions using a dummy variable taking value one when the month appears as a recession month in the NBER recession dating. The main results when controlling for expected growth do not present only present marginal quantitative variations.

In the model, a key role is played by the dual mandate of the monetary authority. Would the monetary authority only care for one dimension, inflation, the correlation between inflation and both uncertainty and risk aversion must vanish. As the tradeoff between inflation and output gap (unemployment) would not present in this case, there must be only one regime. To test this implication of the model, I use the case of Germany. The Bundesbank (and later the ECB) has only one mandate, to control inflation. I repeat the estimations for Germany for the period 1970-2010, and find only one significant regime (i.e. the probability of this regime is one in all periods), as the model suggests.

While I assume that agents use realized inflation to update beliefs on the probability distribution of the rare events, there is no a priory reason to exclude other potential signals. For example. one of particular interest is the nominal interest rate. To control for other potential signals I create a set including different interest rates, term spreads and default spreads. Given the high correlation of these variables I estimate the first principal component of the set, and use it as another regressor in the Markov Switching regime estimations (along with inflation level and inflation volatility). I find that the robust variable is inflation, being the only variable significant in all states. What is more, I argue that since the first principal component is related to a nominal discount rate, the fact that this vector is either non significant or significant but with the incorrect sign, goes in favor of the rare-event approach against the behavioral money illusion approach.

Particularly interesting is what happens in the 2008-2010 recession. From mid-2008 on, the probability of Regime-1 remains close to one. The estimation suggests that agents are concerned with the low-inflation commitment of the Fed under the recovery phase. Some agents are betting on returning to a scenario of high inflation level and volatility in the future. Proofs of this are current discussions about Fed independence, the relation of the Fed and the Treasury, and the ability of the Fed to tight monetary policy once the recovery starts. In fact, in the last months, inflation has been a hot discussion topic as deflation. Note that the model suggests that increases in monthly inflation will affect real stock prices negatively, conditional on expected dividend increases.

The rare-event literature has primarily focused on explaining the equity premium. Rietz (1988), showed that infrequent and large drops in consumption can increase the theoretical equity premium, matching it with the empirical estimations without the requirement of an improperly high risk aversion coefficient. Recent research has continued this line, like in the papers of Barro (2009); Barro and Ursua (2008); Gabaix (2008); Gourio (2008). While most of the rare disaster literature has assumed a constant probability of disaster (see e.g. Rietz 1988, Barro 2009), only a couple papers have worked with time-varying rare event probabilities. While Gabaix (2008) assumes that the degree to which dividends respond to disaster varies in time, Wachter (2009) assumes time varying disaster probabilities, and recursive preferences, in order to explain excess stock market volatility.

The paper is organized in the following way. In Section 2, I present a simple framework in which realized inflation correlates negatively with stock prices when agents use inflation as a signal or proxy for the probability of stagflation. In Section 3, I estimate the unconditional rare-event probability when agents infer it from the monthly inflation distribution. I assume the inflation tail distribution follows a Power Law distribution, and compare results for the US and Germany. I also present the equity pricing implications of agents update the probabilities of the bad state of the world using realized inflation. Section 4 introduces a Markov switching regime estimation to test the relation between inflation and real stock prices. Section 5 tests whether the approach suggested in this paper is more robust than money illusion in order to explain the inflation-stock price puzzle. In Section 6, I test whether the results are robust for the 2007-09 crisis. Section 7 concludes.

2.2 Inflation as a Signal for the Bad State and Stock Prices

Most of the rare disaster literature has assumed a constant probability of disaster (e.g. Rietz 1988 and Barro 2009). Recently, a few articles have worked with time-varying rare event probabilities. For example, Gabaix (2008) assumes that the degree to which dividends respond to a disaster varies in time; while Wachter (2008) assumes time varying disaster probabilities and recursive preferences in order to explain excess stock market volatility.

I introduce a simple two-period model, in which there are two states of the economy, a good state and a bad state. The bad state is characterized by a sharp decrease in stock payout. The probability of the rare event varies in time, and assume that monthly inflation is a proxy (signal) for the time-varying probability of the bad state. The probability of the rare-event (bad state) depends on the realized inflation rate and the variance on the realized inflation volatility. Thus, higher inflation level correlates negatively with real stock prices in this partial equilibrium setup. As shown below, the ex-ante effect of inflation volatility can be both positive or negative for stock prices.

2.2.1 Setup

There are two periods: $t = 0, 1$, and two states of nature: a good state in which a stock pays dividend f at $t = 1$ and a bad state in which the stock pays $f(1-b)$ at $t = 1$, where $1 > b > 0$. Assume that the dividend is Normal distributed with mean $\tilde{f}$and variance $\frac{1}{\tau_0}$: $f \sim N(\tilde{f}, \frac{1}{\tau_0})$. Conditional on being in the good state, the probability of changing state is ρ, such that $0 < \rho < 1$. The key assumption is that the probability of the bad state correlates positively with inflation: $corr(\rho, \pi) > 0$, where π is the realized inflation rate $t = 0$. I assume the existence of a function λ which domain is the real number space, such that $\rho = \lambda(\pi)$ with the following properties: $0 < \lambda(\pi) < 1$; $\lambda'(\pi) > 0$; and $\lambda''(\pi) < 0$.

The precision of the signal depends on realized inflation volatility. If the volatility of the inflation rate is high the precision of the signal is low. The variance of the signal is $\zeta(\sigma_\pi)$, where σ_π is the volatility of the realized inflation, and ζ is a function that relates the variance of the realized inflation to the variance of the signal, such that: $\zeta'(\sigma_\pi) > 0$, $\zeta''(\sigma_\pi) \leq 0$.

The expected value at $t = 0$ for next period dividend is

$$E_0(f) = (1-b)f\rho + f(1-\rho)$$

which can be written as

$$E_0(f) = \tilde{f}\,[1 - b\lambda(\pi)] \tag{2.1}$$

The variance of the dividend can be expressed as

$$Var(f) = (1-\lambda(\pi)b)^2 \frac{1}{\tau_0} + \frac{1}{\tau_0^2} b^2 \zeta(\sigma_\pi) + b^2 \zeta(\sigma_\pi) \frac{1}{\tau_0} \tag{2.2}$$

From Equation 2, note that the variance of expected dividend increases with the variance of the realized inflation and decreases with the inflation level,

$$\frac{\partial Var(f)}{\partial \sigma_\pi} > 0 \tag{2.3}$$

$$\frac{\partial Var(f)}{\partial \lambda(\pi)} < 0 \tag{2.4}$$

As seen in Figure 2.3, monthly inflation volatility has presented peaks either with high inflation (1970's) or low inflation (2000's). This means that, a priory, the effect of inflation on the signal volatility might have an undetermined sign. One the one side, higher inflation decreases the variance of dividends, and therefore stock price should increase. On the other side, higher inflation volatility increases the variance of dividends, therefore stock price should decrease.

2.3 Inflation, Stagflation Beliefs and Stock Prices

In Section 3.1, I estimate the unconditional (time-independent) probability of suffering a stagflation period. Assuming that the tail distribution of monthly inflation rates follows a Power Law, I estimate the probability of stagflation and compare the cases of US and Germany. In Section 3.2, I introduce a Bayesian belief updating model, in which agents infer the time-varying probability of the bad state[7]

[7] Cecchetti et al. (2000) present a model in which agents have permanently dis-

2.3.1 Time-Independent Probability of Stagflation

Assuming that the tail of the monthly inflation distribution follows a Power Law distribution, the cumulative probability of the distribution is

$$F_x(x) = 1 - \left(\frac{x}{x_m}\right)^{-\alpha} \qquad x \geq x_m \tag{2.5}$$

where x is inflation rate, and x_m is a threshold such that for $x > x_m$ the cumulative distribution of x follows Equation (5). The Power Law distribution is often used to model events with fat-tailed distributions. Recently, Barro and Jin (2009) assume that economic disasters (sharp macroeconomic contractions) follow a power law distribution, and estimate the probability of experiencing a 10% contraction in GDP[8]. We are interested in estimating the parameter α[9]. I do so following Clauset et al. (2009). I estimate both α and x_m at the same time, in order to minimize estimation problems (due to finite sample biases)[10]. This approach differs from Barro and Jin (2009), who take x_m as given. That can cause problems while estimating α. If a low value of x_m is chosen, then we have a biased estimate for α. On the other way, if the value of x_m is high, we are loosing data points and

torted beliefs, never learning from experience that low-growth state occurs less than predicted ex-ante, and explain much of the equity premium. Veronesi (2004) shows that adding a learning process to a peso problem hypothesis can explain most if the stock markets' stylized facts. Cogley and Sargent (2008) analyze the case in which agents update their estimates of transition probabilities to a bad state (1930's Great Depression) according to Bayes' law. They include a negative prior (high probability of the bad state) at the beginning of the learning process in order to explain the equity premium.

[8]Other papers introducing power laws in economics and finance are Gabaix (2008), Gabaix and Ibraginov (2009) and Malevergne et (2009).

[9]Taking the derivative of the cumulative probability with respect to α, we can see that when α increases, the probability of having a tail event decreases: $\frac{\partial F_x(x)}{\partial \alpha} = \left(\frac{x}{x_m}\right)^{-\alpha} log\left(\frac{x}{x_m}\right) > 0$

[10]Gabaix and Ibraginov (2009) use least squares, and do not estimate both α and x_m at a time.

therefore increasing the statistical error and bias from finite samples. I follow Clauset el at (2007) in calculating $\hat{x_m}$ so to minimize the distance between the Power Law model and the data[11]. The value for $\hat{x_m}$ is such that the probability distribution of the measured data is as similar as possible to the best-fit power law model (conditional on $x \hat{>} x_m$). With respect to the finite sample bias, Clauset et al. (2009) find that the bias tends to zero as N is higher than 50 observations, being N the observation of x such that $x > x_m$. In the estimations, only in one case N is lower than 50. However, as discussed below, this issue does not prevent the main conclusion of the exercise.

The parameters are estimated for the US, for Germany (two time series, first from 1870 and second from 1960) and the World (which includes all available countries in IMF IFS database from 1960). In Table 2.1 the results are reported. The first row shows the estimations for x_m, the second shows the number of observations for which $x > x_m$, while the point estimate and standard deviation for α are included in the third and fourth rows, respectively. For the US, the point estimate for α is close to 3.19 and for the world (all available countries in IFS database from 1960) is 2.49. As expected, the probability of observing a rare event in the US is thus lower than for the world country-average. We can estimate the expected probability of experiencing a rare event (last row of Table 2.1). The probability of experiencing a month on month inflation rate higher than ten per cent is 0.0005 for the US, while for the world the probability of experiencing inflation higher than ten per cent month on month is 0.1113. In Figure 2.2, the estimated power law distribution for the US is plotted. Note that there is a little deviation at the most extreme values, but the plot suggests an acceptable fit of the data.

I also include the case of Germany. In first place, I work with the period starting in 1870 and ending in 2007; while in second place

[11]In Clauset et al. (2009) the authors use the Kolmogorov-Smirnov statistic to quantify the distance between the two probability distributions.

the starting date is January 1960. Note that when we start the series from 1870, the probability of experiencing inflation higher than 10 percent month on month is 1.5 percent, while when starting from 1960 is 0.03 percent[12], even lower than the US probability. The main difference is that the hyperinflation episode of the 1920s is not included in the sample starting in 1960. Thus, the probability of the extreme event is much lower than when the sample includes the hyperinflation. For a graphic representation of the different rare-event probabilities, I repeat the plot for the fitted distribution but including the cases of Germany since 1870 and since 1960 in addition to the US plot (see Figure 2.3). Note that the US fitted distribution is between the two German cases.

If we take the probabilities as lower bound for the probability of a tail event, we can check their impact on stock prices using the simple model in Appendix I. Suppose that the tail event is to experience a 10 percent monthly inflation rate. Taking the US as the benchmark case, we can see in Table 2.2 that the same stock is priced almost a 10 percent less if agents use the world inflation distribution to calculate the probability of stagflation. Note that such a small probability increase as 0.001 causes the stock price to decrease in nine basis points.

2.3.2 Time-Dependent Probability of Rare Events

Suppose that each state is related to the expected commitment to low inflation of the Central Bank, which at a time could be understood as different probabilities of experiencing tail events. While I acknowledge that the Central Bank commitment to low and stable inflation is endogenous, in this paper I take a myopic stance, and assume the Central Bank is predispose to accept or not certain inflation rates because of other factors, e.g. institutional, political, and the

[12] In this case, the estimation of α may suffer a finite sample bias, since N is below 50 observations. However, note that $\hat{\alpha} + 1.96.std(\hat{\alpha})$ is still above the $\hat{\alpha}$ estimated for the sample starting in 1870.

likes. Historically, the Fed has presented different degrees of commitment to low and stable inflation, and the literature identifies two main periods: the Great Inflation (1970-1984) and the Great Moderation (1984-2007). The probability of observing stagflation in the future when facing an inflation shock might not be the same under a strong low-inflation commitment of the Fed than under a weak commitment. Therefore, if agents update their beliefs on a rare-event using monthly inflation rates, we should observe that the impact of inflation on stock prices should be lower during the Great Moderation (period in which the Fed has a strong commitment to low inflation) than during the Great Inflation period (period in which the Fed has a weak commitment to low inflation).

In order to capture the time-varying commitment of the monetary authority, assume that the Fed loss function is[13]

$$Loss_t = \lambda_t \pi_t + (1 - \lambda_t) y_t \tag{2.6}$$

where λ_t is the time-varying weight on inflation, π_t is the inflation level at time t; and y_t is the output gap at time t. Assuming that the expectations that agents have on the Fed inflation weight can take only two values: $\bar{\lambda}$ (high weight, implying a strong commitment to low and stable inflation) and $\underline{\lambda}$ (low weight, implying a weak commitment to low and stable inflation). In every period, agents form expectations on the Fed commitment to low and stable inflation, $E_t(\lambda_{t+1})$, which enters the inflation distribution prior. If the agents expect a weak commitment, then the impact of inflation on stock prices should be higher than if agents expect a strong commitment to low inflation:

$$corr\left(p_t^s, \pi_t \mid E_t(\lambda_{t+1}) = \underline{\lambda}\right) > corr\left(p_t^s, \pi_t \mid E_t(\lambda_{t+1}) = \bar{\lambda}\right) \tag{2.7}$$

[13] See Cecchetti et al. (2002)

2.3.2.1 Bayesian Belief Updating

As discussed before, the state of the economy is related to the Central Bank commitment to low inflation. The actual state of the economy, $\widetilde{S}$, is not known, and there are M possible states: $\gamma \varepsilon\ (1, M)$[14]. At date t, investors do not know what state the economy is in, and thus form a prior $\pi_s(t) \equiv Prob\left(\widetilde{S} = \gamma \mid \mathscr{F}_t\right)$ where $\mathscr{F}_t$ is the investor's information set at time t. In each state, the probability distribution of a tail event is different. Given a shock, inflation intensity changes conditional on the state. For example, facing a twenty percent increase in the oil price may generate a two percent monthly increase in a weak commitment state, while the same shock may generate a one percent inflation increase in a strong commitment state. Conditional on being in state s, the probability of observing an inflation shock over the next period is expressed as

$$Pr\left[h1_{\{\tau<t\}} = 1 \mid \widetilde{S} = \gamma, \mathscr{F}_t\right] \equiv E\left[h1_{\{\tau<t\}} \mid \widetilde{S} = \gamma, \mathscr{F}_t\right] =$$

$$= \lambda_s(t)\, 1_{\{\tau>t\}}\, dt \tag{2.8}$$

where $\lambda_s(t)$ is the intensity of inflation shocks conditional on being in state γ. Assume for simplicity that $0 < \lambda_s(t) < 1$. The inflation shocks are assumed to be unpredictable, and triggered by the jump of an unpredictable point process $1_{\{\tau>t\}}$ where $\tilde{\tau}$ is the random shock time. Note that it can also be understood as the date-t probability of stagflation conditional on being in state-s. Since investors do not know the actual state of nature, they estimate the actual inflation intensity $\overline{\lambda}^p(t)$ as a as a weighted average

$$\overline{\lambda}^p(t)\, 1_{\{\tau>t\}} dt \equiv E\left[h1_{\{\tau<t\}} \mid \mathscr{F}_t\right] = \sum_{s=1}^{M} \pi_s(t)\, E\left[h1_{\{\tau<t\}} \mid \widetilde{S} = \gamma, \mathscr{F}_t\right] =$$

[14]This section relies on Collin-Dufresne et al. (2010).

$$= \sum_{s=1}^{M} \pi_s(t)\,\lambda_s(t)\,1_{\{\tau>t\}}\,dt \tag{2.9}$$

Consequently, conditional on the investor 's information set, the rare-event probability (inflation intensity) is equal to a weighted average of the conditional rare-event probabilities, being the weights the probabilities of each state

$$\overline{\lambda}^{p}(t) = \sum_{s=1}^{M} \pi_s(t)\,\lambda_s(t) \tag{2.10}$$

Investors update their estimates of $\pi_s(t)$ conditional on observing an event (inflation shock) during the time interval dt. The Bayesian updating process takes the following form (see Lipster and Shiryaev, 2000)

$$d\pi_s(t) = \pi_s(t)\left(\frac{\lambda_s(t)}{\overline{\lambda}^{p}(t)} - 1\right)\left(h1_{\{\tau<t\}} - \overline{\lambda}^{p}(t)\,1_{\{\tau>t\}}dt\right) \tag{2.11}$$

According to Equation (12), when observing an inflation shock over an interval dt, investors revise upwards the probability of states associated with higher inflation intensity ($\lambda_s(t) > \overline{\lambda}^{p}(t)$) and revise downwards the probability of states associated with lower inflation intensity ($\lambda_s(t) < \overline{\lambda}^{p}(t)$).

From now on, I work with only two states of nature, characterized by the Fed commitment to low and stable inflation. In the first state, the commitment is weak, while in the second the commitment is strong. Both, the weak and strong commitment are measured by the amount of output sacrificed in order to keep inflation low. Thus, in state 1, facing a shock, inflation intensity is higher than in state 2: $\lambda_1(t) > \lambda_2(t)$. Being $M = 2$; $\gamma = \{1, 2\}$, and $\lambda_1(t) > \lambda_2(t)$, the updating probability of state 1 (weak commitment to low inflation) is

$$d\pi_1(t) = \pi_1(t)\left(\frac{\lambda_1(t)}{\overline{\lambda}^p(t)} - 1\right)\left(h1_{\{\tau<t\}} - \overline{\lambda}^p(t)\, 1_{\{\tau>t\}}dt\right) \tag{2.12}$$

while the updating probability of state 2 (strong commitment to low inflation) is

$$d\pi_2(t) = -d\pi_1(t) \tag{2.13}$$

Note that given a shock, if the increase in inflation is higher than the average expected inflation intensity ($h1_{\{\tau<t\}} > \overline{\lambda}^p(t)\, 1_{\{\tau>t\}}dt$), then $d\pi_1(t)$ increases, since $\lambda_1(t) > \overline{\lambda}^p(t)$.

2.4 Empirical Implementation

2.4.1 Markov Switching Regime Estimation

I perform a 2-regime Markov Switching estimation, where the regimes are aimed to control for the (agent's expected) low-inflation commitment of the Fed. In Figure 2.4, I plot monthly inflation and its volatility, defined as the last 12-month standard deviation. Volatility remains high until 1991, and then increases again by the end of the decade, spiking by the end of the sample (2008-2009). it is worth to stress that most papers do not find structural change in the inflation series until 1991 (see, e.g., Stock and Watson 2002; Cecchetti et al, 2004).

I estimate the effects on the S&P 500 dividend-price of both headline[15] inflation level and volatility (defined as the last twelve month inflation standard deviation). The data frequency is monthly. I work

[15]For robustness, I also repeat the exercise using: i) core inflation (that is, headline inflation excluding energy and food prices); ii) non-energy inflation (that is, headline inflation excluding energy prices); and iii) non-food inflation (that is, headline inflation excluding food prices).

with both trailing dividends and smoothed dividends by taking the last ten year average. Since I can not reject the presence of a unit root in the dividend series, I use for the estimations the dividend-price ratio in differences, which is a proxy for the inverse of the monthly real stock return. Table 2.5 includes the basic statistics for the monthly inflation, the inflation volatility, the smoothed dividend price ratio (DP_S), the non-smoothed dividend price ratio (DP), and finally the monthly real stock return. The model is

$$d\left(\frac{\tilde{D}}{p}\right)_t = \beta_0^{S_t} + \beta_1^{S_t}\pi_t + \beta_2^{S_t}VOL_t(\pi) + \varepsilon_t \tag{2.14}$$

$$\varepsilon_t \sim N\left(0,\, \sigma_{S_t}^2\right)$$

where $d\left(\frac{\tilde{D}}{p}\right)$ stands the first difference of the stock yield $\left(\frac{\tilde{D}}{p}\right)$. $\tilde{D}$ stands for smoothed dividends. I use the last ten year average of dividends. The independent variables are: realized inflation (π_t) and the last 12-month standard deviation of inflation, $VOL_t(\pi)$, as a proxy for the signal precision. Higher standard deviation is positively correlated with lower signal precision (see Section 3 for the relation between the inflation volatility and signal precision). The error term ε_t is assumed to distribute normally with mean zero and variance $\sigma_{S_t}^2$ [16]. S_t is the state variable which changes through time and cannot be observed by investors. S_t is determined by Markov chain: $Prob\,(S_{t+1} = j \mid S_t = i) = p_{ji}$.

The state-dependant variables to be estimated are β_0, β_1, β_2, σ^2. This way I make the sure that the impact of both inflation first and second moments on the stock-yield is dependent on the state, avoiding the biases arising from imposing only one state. Another key point is that I regress all the variables known at time t. The introduction of lagged variables in this analysis would create biases since the main

[16] For robustness I also assume that ε_t follows a Student-t distribution.

assumption is that agents update their beliefs on an a rare-event using realized inflation while at the same time they are pricing stocks. The inclusion of lagged variables would imply the use of different information sets, including potential biases that may jeopardize the whole point of the estimation exercise. With respect to the sample used, I first analyze the period from 1970 to the end of 2007, in order to avoid the impact of the 2008-09 financial crisis and recession. The complete sample, including this last period is analyzed with proper detail in Section 2.6.

2.4.2 Estimation Results

In Figure 2.5, I plot the regimes smoothed probabilities. Inflation correlates positively with stock yields in both regimes. Regime-1 presents a probability close to one for most of the period 1973-1983. After that, for the period 1984-1988 there is a high volatility in relation to the regime probability. For the 56 months that go from January 1984 to December 1988, 38 show probability of Regime-1 above 0.5. After 1988, Regime-2 is the one with probability close to one until 2007. There are two main exceptions, those being the periods August 1990-April 1991 and July 2002-November 2002. Only for these two periods the probability of Regime-1 is above 0.5. Therefore, a first approximation to the problem shows two regimes: Regime-1 with probability close to one until 1983 while Regime-2 with probability closer to one after 1988, with the two noted exceptions. The period 1984-1987 shows a high fluctuation in regimes[17].

The results from the Markov switching estimation are presented in Table 2.4. For both regimes, an increase in realized inflation correlates negatively with real stock prices. In Regime-1, one basis point

[17]This result is not at odds with the Great Moderation literature. In fact, Stock and Watson (2003) do not find breaks in the inflation series until the second quarter 1991. In this line, Cecchetti et al. (2006) use as a break point 1991 in order to analyze the impact of monetary policy on the macroeconomic performance.

increase in the monthly inflation rate significantly increases the dividend yield in 15.78 basis points, implying a similar decrease in stock prices. For Regime-2, it is still the case that an increase in the monthly inflation rate correlates positively and significantly with a higher dividend yield. However, a one basis point increase in the monthly inflation rate increases the stock yield in 7.17 basis points, less than a half of the coefficient in Regime-1. Thus, when inflation increases, the probability of experiencing an extreme event in the future decreases today's stock price. It is worth to note that the coefficient for inflation in Regime-1 is statistically different from the one in Regime-2.

The two estimated regimes are associated to the agents' expected reaction of the Fed, in particular to the Fed commitment to low and stable inflation. In Regime-1 this commitment is weaker than in Regime-2. What is more, the Regime-1 probability is high during the Great Inflation period, while Regime-2 probability is high for the Great Moderation period. From the estimation a regime fluctuation is clearly present. These results go in the line of Bianchi (2009). The author argues that the Fed policy has fluctuated between what he calls a Hawk and a Dove regime. In the first one, the Fed minimizes inflation while in the second one minimizes output fluctuations. What this paper and Bianchi paper have in common is the possibility of having reversible regime changes, and that agents are aware of this possibility, therefore forming expectations according to the Fed policy. When testing the model allowing for one-for-all regime change, the turning month is September 1984. This result also coincides with Bianchi (2009), who finds a regime change in 1984.

As emphasized in Section 2.3.2, if agents use realized inflation as a signal, the volatility of inflation should also be a relevant piece of information. The estimation output shows non-significant coefficients for the last 12-month standard deviation of monthly inflation[18]. The

[18]The results on the inflation volatility do not depend on the volatility definition. The results are the same if volatility is defined as last 12-month, 6-month or 24-

sign of the coefficient in Regime-1 also shows a puzzling result. A negative signs implies that higher signal volatility affects positively stock prices. In Regime-2 the positive sign of the coefficient is as expected.

So far, I the results presented are for the first difference in the smoothed dividend yield. I repeat the estimation for the smoothed dividend yield (not in differences) and the non-smoothed dividend yield (both in levels and in differences) in order to show that the election of the dependant variable is not driving the results (see Table 2.5). The results are pretty robust for Regime-1. For Regime-2, the non-stationary of the series is the main explanation for having non-significant (and with wrong signs) coefficients for inflation. Moreover, the estimated coefficients do not vary much if using smoothed or non-smoothed dividend yields.

To sum up, the two regime estimation is useful for showing: i) that higher inflation correlates with lower stock prices; ii) that Regime-1 is associated with a weak expected Fed commitment to low-inflation; iii) that regimes fluctuate in time, although Regime-1 has a higher probability during the Great Inflation period and Regime-2 during the Great Moderation period; iv) that the correlation between realized inflation and real stock prices is higher in Regime-1 than in Regime-2, as the Bayesian updating model in Section 2.3 suggests; v) that the signal precision comes not be to significant.

2.4.3 Controlling for Expected Economic Growth

Several variables that account for expectations on economic growth are included so to control for expected real economic activity in the regressions. The first two measures are built from the Livingstone Survey[19]. One measure is the expected real GDP growth rate for next

month standard deviation of the monthly inflation rates.

[19]The Livingston Survey was started in 1946 by Joseph Livingston. It is the oldest continuous survey of economists' expectations. It summarizes the fore-

two quarters (EGDP_2Q). The other measure is the expected GDP growth rate for the 12-month-ahead forecast minus the the 6-month-ahead forecast (EGDP_4Q-2Q). This second measure aims to control for the expected cycle of the GDP, that is, the persistency of growth rates.

Another source of agent's expectations on real GDP growth rates is the Survey of Professional Forecasters[20]. While the frequency of this dataset is higher than the Livingstone one (quarterly frequency), the sample starts in the third quarter 1981, which is a problem since the relevant period for this period starts in 1970. In Figure 2.6, I plot the three series. Note that the correlation between the expected quarterly GDP growth rates coming from the Livingston Survey and the Survey of Professional Forecasters is high, in particular taking into account the frequency difference.

I also include in the regressions the Anxious index (ANX) from The Federal Reserve Bank of Philadelphia. The index refers to the probability of a decline in real GDP, as reported in the Survey of Professional Forecasters. The index often goes up just before recessions begin, peaks during recessions, and then declines when recovery seems close.

In Table 2.6, I report the results when including controls for expectations on economic activity in the regressions. First, in the three specifications presented in the Table 2.6, the coefficients for the realized monthly inflation are significant, with the one corresponding to Regime-1 being higher than the one for Regime-2, as expected. What is more, in the three specifications, the inflation coefficients for

casts of economists from industry, government, banking, and academia. The Federal Reserve Bank of Philadelphia took responsibility for the survey in 1990. See http://www.phil.frb.org/research-and-data/real-time-center/livingston-survey/.

[20]The Survey of Professional Forecasters is the oldest quarterly survey of macroeconomic forecasts in the United States. The survey was conducted by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990.

Regime-1 are statistically different from the ones in Regime-2. Consequently, the main results remain robust to the inclusion of expected real activity variables. Inflation volatility remains non-significant. The variables controlling for real activity expectations also show expected signs. The first one, next quarter expected real GDP growth, controls for the trend growth of the economy. In other words, if agents expect a positive growth rate for next quarter, means that the actual quarter is below potential, so stock prices are low. On the other side, if agents expect negative growth rates for next quarter, then stock prices are high and will adjust to lower levels. It is worth to emphasize that the frequency of the data is biannual, so the frequency has a lot to do with the present explanation. On the other side, the second measure (EGDP_4Q-2Q) aims to control for the persistence of the deviations (ie, the economic cycle). In this case, negative expectations should correlate with lower stock prices. The results show that for Regime-1 the signs of the coefficients are as expected, and significant. However, for Regime-2 the coefficients are not significant. This may be explained by the lower macroeconomic volatility that the US economy experienced since 1991 (until 2007).

The bottomline is that realized inflation still has explicative power, even when controlling for expected economic activity. The correlation of inflation and real stock prices can not be explained by expected economic activity, the omitted variable that drives Fama proxy hypothesis.

Finally, in Table 2.7, I report the results of the estimation when including a dummy variable for recessions. The dummy takes the value one when the month is consider as a recession month by the NBER Business Cycle Dating Committee, and zero otherwise. When including the dummy, the results show an interesting twist. First of all, the coefficients for inflation remains with the expected sign and significant (except for Regime-1 in specification 2). An increase in one basis point in inflation decreases stock returns between 8 and 10 bps. Noteworthy, the coefficients are no more statistically different between regimes. During recessions, the correlation between inflation and real stock prices increases significantly. In fact, an inflation increase in 1 bp decreases real stock prices around 23 bps in Regime-1 and 19 bps in Regime-2. Regime-1 still shows higher covariance between inflation and stock prices, but not statistically significant. In any case, the bulk of the correlation between inflation and stock prices seems to take place during recession periods, for both regimes.

2.4.4 Other Inflation Measures

So far I have worked with monthly headline CPI inflation, that is, inflation including both energy and food price variations. Since mid-nineties, central banks have been paying attention to inflation measures that exclude its most volatile components, particularly energy and food prices. In Figure 2.7, I plot the monthly inflation series for headline CPI, core, non-energy and non-food. In the lower figure I plot the inflation volatility, again defined as the last 12-month standard deviation. Both the headline and the non-food inflation volatility present spikes in the years 1987, 1991 and from 2000 on. On the other side, the series for core inflation and non-energy inflation present low volatility since 1983. I repeat the 2-regime Markov switching estimations using core inflation, non-energy and no-food inflation. The results for the core inflation estimations are included in Table 2.8, and for non-energy inflation in Table 2.9. Results for non-food inflation and similar to the headline CPI results, so they are not reported.

The coefficients for core inflation are only significant in Regime-1. A one bp increase in core inflation decreases stock prices between 13 and 19.4 bps. For Regime-2 only when interacting the inflation variable with the recession dummy the coefficient is significant (see specification 5). In that case, during recession, an increase of one bps in core inflation decreases stock prices in 13.9 bps.

The results when using non-energy inflation are pretty similar to the results using headline inflation. In both regimes inflation is significant. In Regime-1, a one bp increase in the monthly inflation rate decreases stock prices between 15.9 and 23.5 bps. In Regime-2 the results are statistically lower, with figures between 8.3 and 5.2 bps. Therefore, the impact of realized inflation on real stock prices is robust to different inflation measures, although core inflation only seems to correlate negatively with stock prices during recessions.

2.4.5 The German Case

In the model, the time-varying commitment of the monetary authority exists because of its double mandate, to stabilize both inflation and unemployment. Would the monetary authority only have one mandate, to stabilize inflation, then the CB loss function is

$$Loss_t = \lambda_t \pi_t \tag{2.15}$$

where λ_t is the time-varying weight on inflation, π_t is the inflation level at time t. In this specification, the weight on inflation must be equal to one, $\lambda_t = 1$. In this case, the testable model implications are: i) real stock prices would decrease with increasing inflation rates; ii) only one regime is significant.

Table 2.10 presents the results when testing the model for the German case. The mandate of the Bundesbank (before the Euro) and the ECB is unique: to control inflation. The estimation shows that there is only one significant regime (in this case denominated Regime A), given that the probability of Regime A in all periods is one. As expected, the estimated inflation coefficient is positive. The estimated coefficient for inflation volatility is negative. In the German case, an increase in inflation volatility leads to higher real stock prices, which is an unexpected result. Negative coefficients for inflation volatility are found in some US specifications but for the low commitment regime, and in all cases they are not significant.

2.5 Testing Other Nominal Signals

A fair question would be why investors only use realized monthly inflation rates in order to update their beliefs on the probability of a stagflation event rather than using other variables. In fact, financial variables have higher frequencies than inflation, and therefore may be a better proxy for the probability of an extreme event in the future. In this paper, I use realized inflation because of two main reasons: (i) it is the relation between inflation and stock prices what has puzzled the literature; (ii) the event of interest is related to inflation episodes themselves (stagflation / hyperinflation). However, it is still the case that other financial variables might also be used as a proxy for the probability of an extreme-event. Therefore, in this section I incorporate a third regressor in the Markov Switching Regime estimation that attempts to incorporate the information enclosed in a set of financial variables that span the investment opportunity set, other than monthly inflation rates. This variable corresponds to the first principal component of the space spanned by different interest rates, including long and short term rates, term spreads, default spreads, etc. The main point is to test if the information included in the inflation rate is also included in the investment opportunity set, or if inflation also endorses more information relevant for the agent.

This analysis also relates to money illusion, and in particular to test if the idea of agents updating beliefs on a bad state of the world using inflation has more explicative power than the money illusion approach. In order to explain the stock price-inflation puzzle, the behavioural approach relies on money illusion. The basic story is that investors confuse nominal and real discount rates. Thus, given future real cash flows, higher inflation leads to higher discount rates (nominal interest rates), and therefore to lower stock prices (e.g. Modigliani-

Cohn, 1979; Campbell & Vuolteenaho, 2004; Brunnermeier and Julliard, 2007; Schmeling and Schrimpf, 2008).

While money illusion is very difficult to test empirically, at least we can test some of its implications. The most popular of the money illusion hypothesis implications is the one that states that agents confuse real and nominal discount rates. If so, an increase in realized (expected) inflation increases the nominal discount rates. Conditional on future real cash flows, the present value of the cash stream decreases just by the effect of inflation. By regressing at a time the realized monthly inflation and a set of nominal interest rates, I argue that the Modigliani and Cohn (1979) hypothesis is tested. If money illusion is the ruling explanation, then nominal interest rates should be significant and not monthly inflation. However, if inflation is actually used as a proxy for the probability of stagflation, then the opposite results are expected.

2.5.1 Investment Opportunity Set

First, the investment opportunity set (IOS) is created, including the following variables: market yield on U.S. Treasury securities at 1, 3, 5, 7, 10, -year constant maturity; a term spread (15yr-1yr); 3, 6, -month Treasury bill secondary market rate discount basis; average majority prime rate charged by banks on short-term loans to business; average rate on 1-month negotiable certificates of deposit (secondary market); average rate on 3-month negotiable certificates of deposit (secondary market); average rate on 6-month negotiable certificates of deposit (secondary market); Federal funds effective rate; Moody's yield on seasoned corporate bonds-AAA; and finally the Bond buyer GO 20-bond Municipal Bond Index. All data is from FRED, monthly date from 1970 until 2007.

I decompose the IOS using principal components[21] and use the

[21] For a review on principal componet estimation see Bai and Ng (2007) and Ng and Ludvigson (2009).

first principal component as a regressor in the Markov Switching Regime estimation, in addition to the realized level and volatility of the monthly inflation rate. The principal components is estimated in a static way[22]. The estimation shows that the first principal component of the IOS is capturing more than 80 percent of the common volatility. The correlation between the first principal component and inflation monthly rates is close to 0.47 (see Figure 2.9 for a plot of the first principal component and inflation).

2.5.2 Markov Switching Regime Estimation

As in the previous sections, a 2-regime Markov Switching model is estimated. The difference is that a third regressor $PC\,1_t$ is included, which is the first principal component of the Investment Opportunity Set. The model to be estimated is

$$d\left(\frac{\tilde{D}}{p}\right)_t = \beta_0^{S_t} + \beta_1^{S_t} PC1_t\,1 + \beta_2^{S_t}\pi_t + \beta_3^{S_t} VOL_t(\pi) + \varepsilon_t$$

$$\varepsilon_t \sim N\left(0,\, \sigma_{S_t}^2\right)$$

$$Prob\,(S_{t+1} = j \mid S_t = i) = p_{ji}$$

$$S_t = 1,\, 2$$

[22]Boivin and Ng (2005) find that static and dynamic principal components have similar forecast precision, but static principal component are much easier to compute. What is more, the majority of factor augmented regressions use static factor estimates (see e.g. Ng and Ludvigson 2009). Another aspect is that since N (the number of time series in the IOS) is not close to infinite the estimation might be imprecise. However, using a Markov Chain Monte Carlo (MCMC) approach, Ng and Ludvigson (2009) show that the bias is not that important.

The estimation results are in Table 2.11. As before, Regime-1 is the regime in which agents expect a weak low-inflation commitment from the Fed, Regime-2 a strong low-inflation commitment. Inflation correlates positively with stock yield first difference in both regimes, even after controlling for the information included in the first principal component of the investment opportunity set. In Regime-1, a one basis point increase in the monthly inflation rate significantly increases the dividend yield between 14 and 21 basis points. In Regime-2, a one basis point increase in the monthly inflation rate increases the stock yield between 8 and 9 basis points.

The first principal component of the IOS is significant in both regimes. However, note that in Regime-2 the sign is negative in all specifications, implying that stock prices increase when the principal component is high. This is at odds with the money illusion hypothesis endorsed by Modigliani and Cohn (1979). Therefore, I argue that empirically the money illusion story is not strong enough as previous papers suggest.

To sump up, the inflation channel is still present when controlling for other potential proxies for the probability of the rare event. Moreover, I understand this piece of evidence as supporting that realized inflation is relevent per se, and not because of nominal discount rates and agents suffering from money illusion.

2.6 2008-2010: Crisis, Recession and Stagflation Probability

In this section I incorporate the crisis years 2009 and 2010 to the estimations. In Table 2.12, I present the results from the estimations. When including the period 2008-2009 in the 2-regime estimation, the inflation coefficients are still positive and significant, with the coefficient in Regime-1 slightly higher than the coefficient in Regime-2. However, the coefficients are not statistically different between regimes. The signal volatility is positive in both regimes, and marginally significant in Regime-2.

Particularly interesting is what happens in the current recession. As seen in Figure 2.10, in the last months of the sample the probability of Regime-1 is close to one. As explained before, the estimation suggests that agents are concerned with the Fed commitment to low-inflation once the recovery phase is in place. Therefore, some agents are betting on returning to a scenario of high inflation level and volatility in the future. In fact, in the last months, inflation has been a hot discussion topic as deflation. For example, recently some hedge funds seem to bet on hyperinflation. In June the WSJ wrote: "A hedge fund firm that reaped huge rewards betting against the market last year is about to open a fund premised on another wager: that the massive stimulus efforts of global governments will lead to hyperinflation"[23]. In another article, the WSJ stresses [24]: "One nightmare keeping many investors awake at night is the prospect that heavy government borrowing and spending, along with super-easy Federal Reserve monetary policy, will eventually crush the value of the dollar, fueling hyperinflation." Finally, discussions about the Fed independence and in particular on the Fed commitment to tight monetary policy once the recovery starts have spread trough the media. Editorial columns ask boldly things as: 'Does anyone really believe the Fed will contract the money supply as the economy starts to show growth?' [25]. Thus, the idea that in Regime-1 the expected commitment of the Fed to low and stable inflation is under question seems to have anecdotal support. In this regime, increases in monthly inflation will have a negative impact on real stock prices. However,

[23]"Black Swan Fund Makes a Big Bet on Inflation", WSJ, June 1st 2009

[24]"Make Money, Whatever Happens to the Economy", WSJ, July 26th 2009

[25]"Bernanke's Exit Dilemma", George Melloan, WSJ, August 4th 2009.

inflation will be correlated with recovery probabilities, so it will be very interesting to be able to disentangle both effects.

2.7 Conclusions

In this paper I suggest an explanation for the negative correlation between real stock prices and inflation: agents use realized inflation rates as a proxy for the probability of a rare-event, namely high inflation accompanied by null or negative economic growth (stagflation, or hyperinflation in the limit). When agents observe higher inflation rates, the probability of experiencing stagflation increases as shown in a simple Bayesian model. Consequently, agents demand a higher expected premium (lower stock price).

Particularly important are expectations on the monetary authority commitment to low inflation. In the model, the monetary authority has a dual mandate on inflation and unemployment. In other words, the Fed loss function depends on the inflation rate and the output gap. In every period, the agents form expectations on the Fed commitment to low and stable inflation. If the agents expect a weak commitment to low inflation, the probability of stagflation in the future increases, and thus the effect of a one basis point increase in realized inflation on stock prices should be higher than in the case where agents expect a strong commitment to low inflation.

I estimate a Markov switching regime model with two regimes to test the correlation between realized inflation and stock prices. I identify both regimes in the following way: Regime-1 is when agents expect a weak Fed commitment to low-inflation; while in Regime-2 agents expect a strong Fed commitment to low-inflation. In Regime-1, a one basis point increase in realized inflation translates into 15.8 basis point decrease in the real stock return, while in Regime-2 the impact is of 7.2 basis points (the coefficients are statistically different between regimes).

I find a clear regime change by 1991. While this may seem puzzling, it is worth to emphasize that seminal papers on the Great Moderation only find breaks in inflation time series by 1991 (see e.g. Stock and Watson 2003 and Cecchetti et al. 2006). What is more, my estimation results show that in every recession the probability of the Regime-2, the one in which the correlation of inflation and stock prices is lower, strongly decreases. Facing a recession agents tend to weight more the probability of the FED relaxing its inflation commitment. In fact, this is clearly a rational way to think about the issue, since the worst scenario for the FED is a deflation, as has been proved during the recent financial crisis.

An increase in inflation rates when the economy is in recession may also be understood as positive news. If demand is increasing more than supply, then the increase in prices may be signaling the end of the recession. To control for this effect, I include in the estimations expected variations in production. I use expected variations in GDP coming from surveys, both the Livingstone survey and Professional Forecaster survey. I also control for recessions using a dummy having the value one when the month appears as a recession month in the NBER recession dating. The main results hold with marginal variations.

In the model, a key role is played by the dual mandate of the monetary authority. If the monetary authority only cares for one dimension, inflation, then the correlation between inflation and both uncertainty and risk aversion must vanish, since there should exist only one regime. To test this implication of the model, I use the case of Germany. The Bundesbank (and the ECB since the Euro introduction), only has one mandate, to control inflation. I repeat the estimations for Germany for the period 1970-2010, and find only one significant regime, as the model suggests.

For the 2008-10 crisis, I read the results as agents being concerned on the degree of commitment of the Fed to low and stable inflation once the economic recovery is in place. Some agents were betting on returning to a scenario of high inflation level and volatility in the future. Proofs of this are discussions about the independence of the Fed, the relation of the Fed and the Treasury, and the ability of the Fed to tight monetary policy once the recovery starts. In fact, during 2009, inflation has been a hot discussion topic as deflation in the media.

Finally, I test one of the most popular money illusion hypotheses, the one that states that agents confuse real and nominal discount rates. In order to do so, I estimate the model again, but adding a third regressor. This third regressor is the first principal component of a set of nominal discount rates (including long and short interest rates, etc). I find that the first principal component is significant in both regimes, but presents an unexpected negative sign in Regime-2, which is at odds with the behavioural approach. On the other side, realized inflation is significant in all regimes and correlates negatively with stock prices. I understand this piece of evidence as supporting that realized inflation is relevant per se as a signal on the probability of stagflation, and not because of nominal discount rates and agents suffering from money illusion as previous papers suggest.

Figure 2.1: Stock Yield and Monthly Inflation

Seasonally adjusted CPI monthly variations and dividend-price ratios

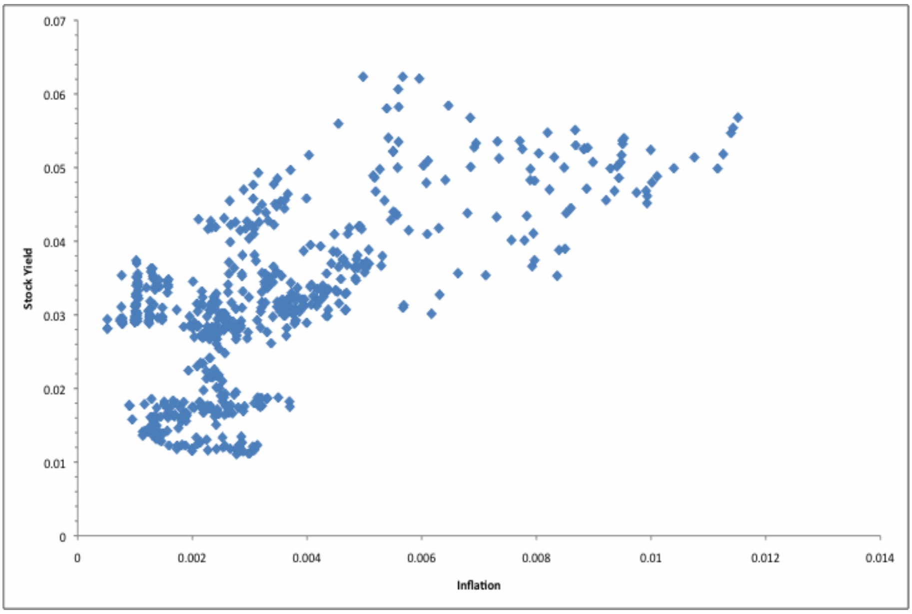


Figure 2.2: **Monthly Inflation and Power Law Distribution for US**

Notes: The figure plots (on log axes) the data contained in the US monthly inflation distribution and a power-law distribution of the form $p(x) = Cx^{\alpha} \quad for\, x \geq x_m$. The points represent the cumulative density functions P(x) for a for a synthetic dataset distributed according to a power law with $\alpha = 3.19$ and $x_m = 0.0091$. Solid line represents best fit to the data using the methods in Clauset et al (2009).

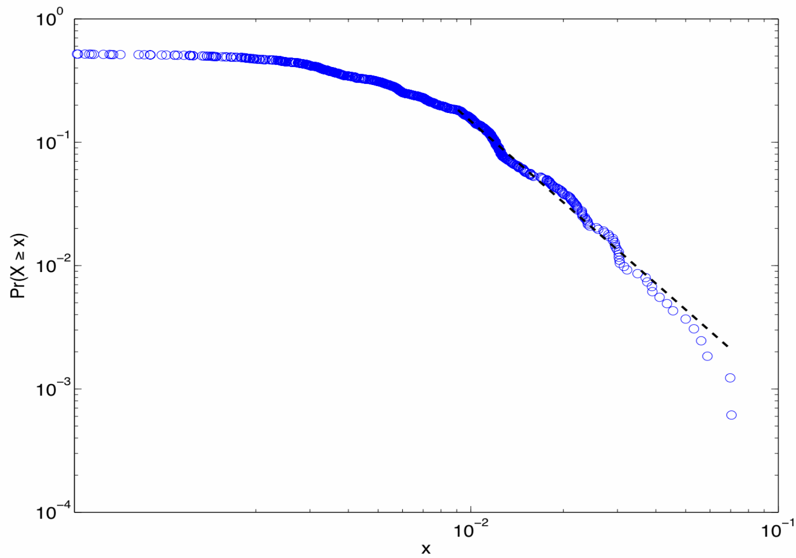


Figure 2.3: **Monthly Inflation and Power Law Distribution**

Notes: The figure plots (on log axes) the data contained in the US (red); Germany since 1870 (green); and Germany since 1960 (blue), monthly inflation distribution and a power-law distribution of the form $p(x) = Cx^{\alpha} \quad for\; x \geq x_m$. The points represent the cumulative density functions P(x) for a for a synthetic dataset distributed according to a power laws estimated in Table 2. Solid line represents best fit to the data using the methods in Clauset et al (2009).

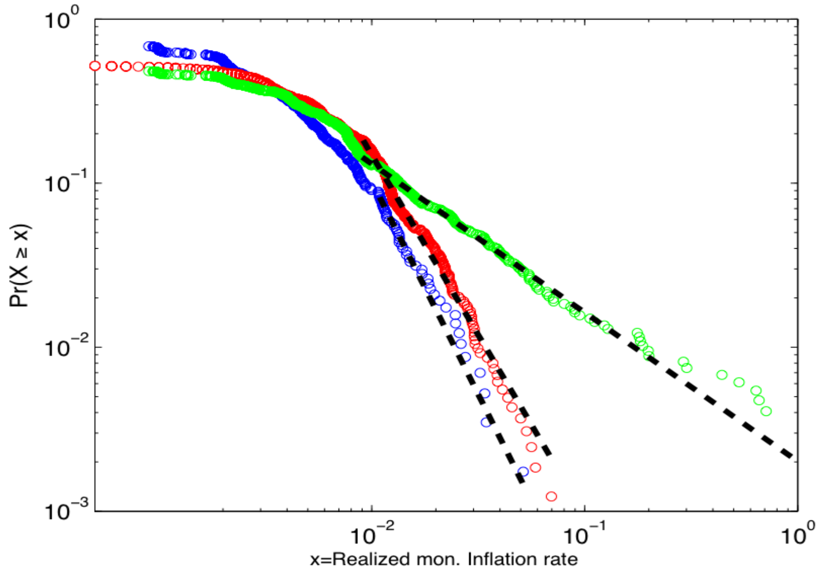


Figure 2.4: Monthly Inflation Level and Volatility

Notes: Seasonally adjusted headline CPI monthly variations. Inflation volatility is measured as last twelve months standard deviation. Headline CPI includes food and energy prices.

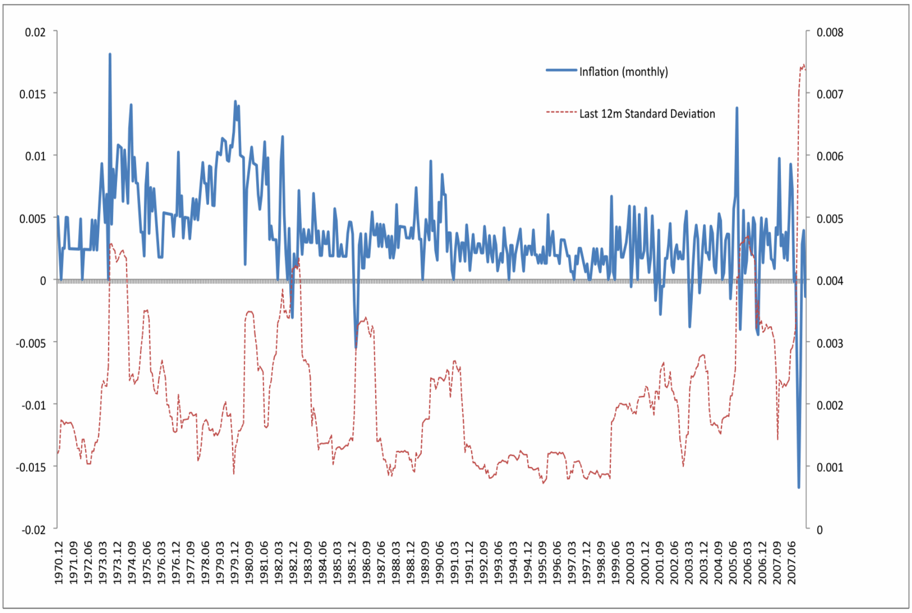


Figure 2.5: **Smoothed State Probabilities**

Notes: Dependent variable is the first difference of the stock yield, where the dividends are smoothed taking the last ten year average: $d\left(\frac{\tilde{D}}{P}\right)_t = \beta_0^{S_t} + \beta_1^{S_t}\pi_t + \beta_2^{S_t} VOL(\pi)_t + \varepsilon_t$. $S_t = 1, 2$ is the state variable which changes through time and cannot be observed by investors. S_t is determined by Markov chain: $Prob\ (S_{t+1} = j \mid S_t = 1) = p_{ji}$. The upper panel of the Figure shows the smoothed probabilities for Regime 1, and the lower panel shows smoothed probabilities for Regime 2.

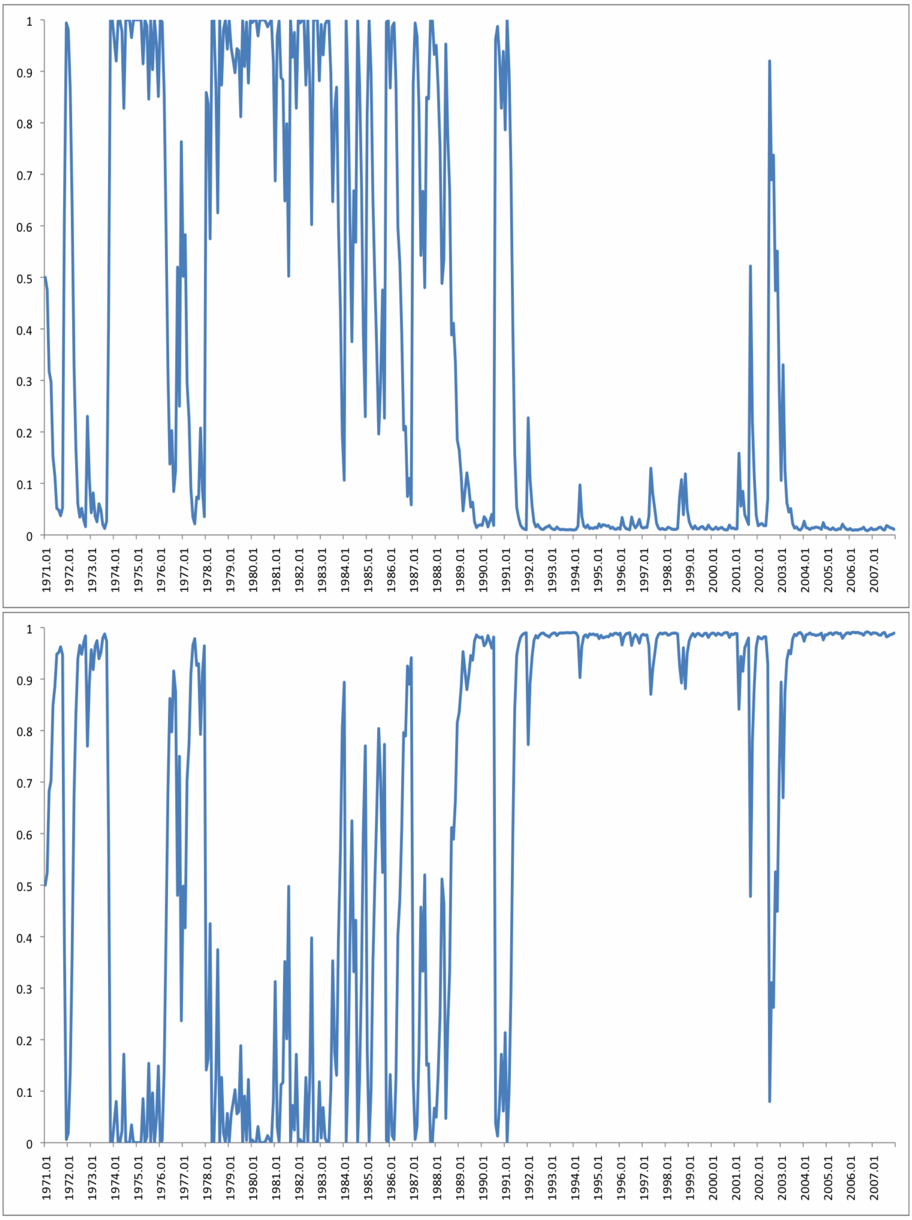


Figure 2.6: Expected Real Activity Indices

Notes: The first measure is the expected real GDP growth rate for next two quarters (EGDP_2Q). The second measure is the expected GDP growth rate for the 12-month-ahead forecast minus the the 6-month-ahead forecast (EGDP_4Q-2Q). This second measure aims to control for the expected cycle of the GDP, that is, the persistency of growth rates. Both measures are from the Livingston Survey. Expected Growth Professional Forecasters is source of agent's expectations on real GDP growth rates is the Survey of Professional Forecasters. While the frequency of this dataset is higher than the Livingstone one (quarterly frequency), the sample starts in the third quarter 1981, which is a problem since the relevant period for this period starts in 1970.

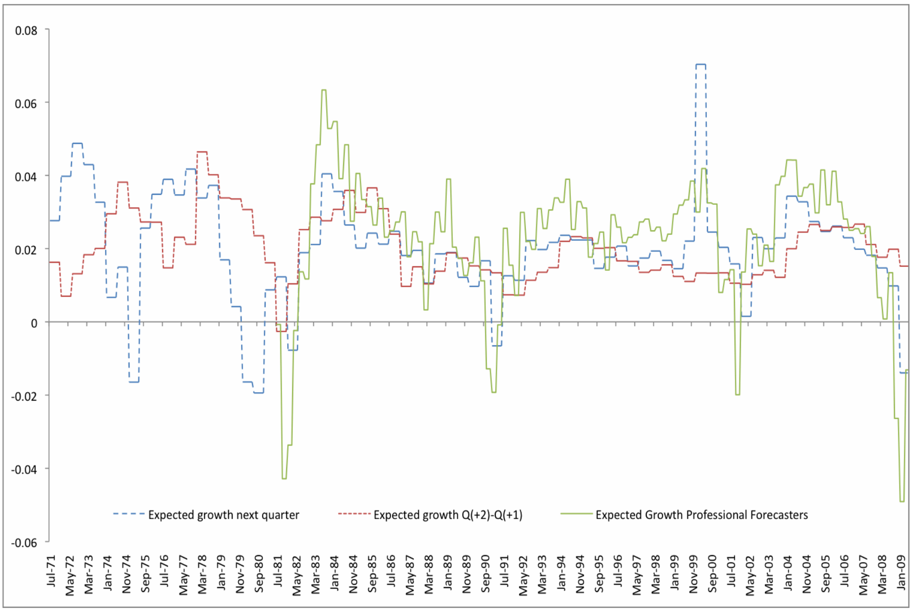


Figure 2.7: Monthly Inflation: Level and Volatility

Notes: The upper panel shows seasonally adjusted CPI monthly variations, and the lower panel the volatility measured as last twelve months standard deviation. Data from FRED. Headline Inflation corresponds to CPI including all components. Non Food is the realized inflation rates excluding food prices; non energy is the realized inflation excluding energy prices; and Core is the realized inflation rates excluding both food and energy prices.

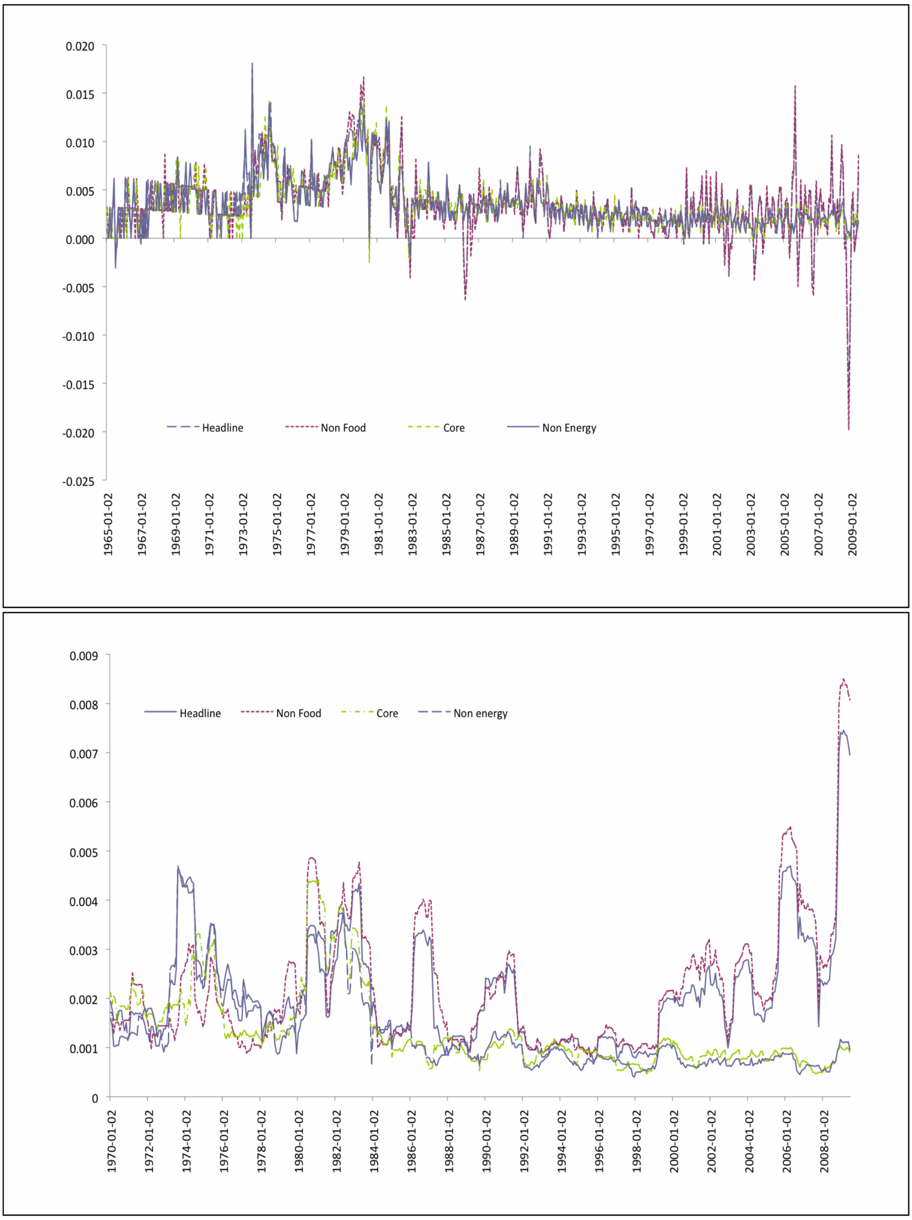


Figure 2.8: Investment Opportunity Set First PC and Inflation Rates

Notes: the figure shows monthly inflation rate and the first principal component of the Investment Opportunity Set, which is a set of various nominal interest rates (see IOS definition in Section 6.1). The first principal component of the IOS is capturing more than 80 percent of the common volatility.

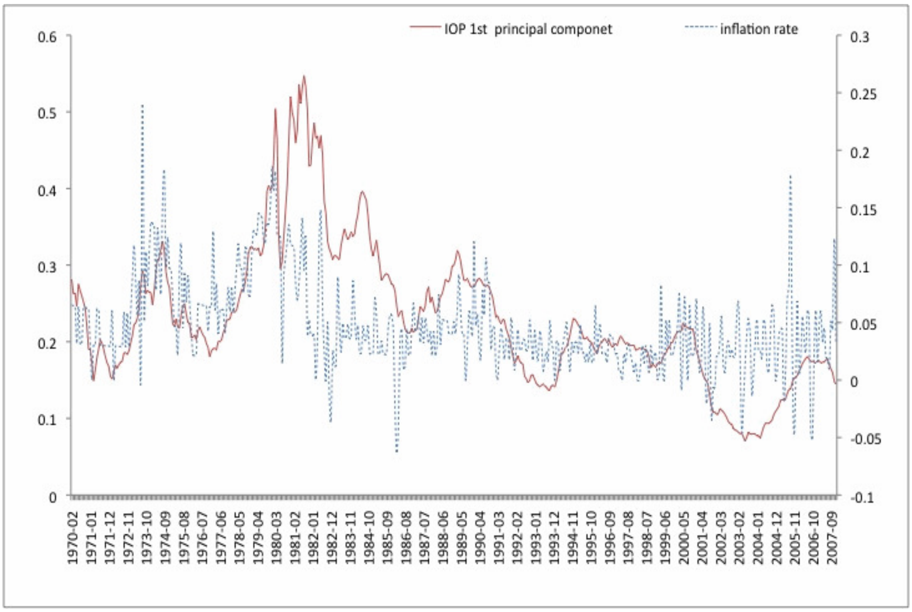
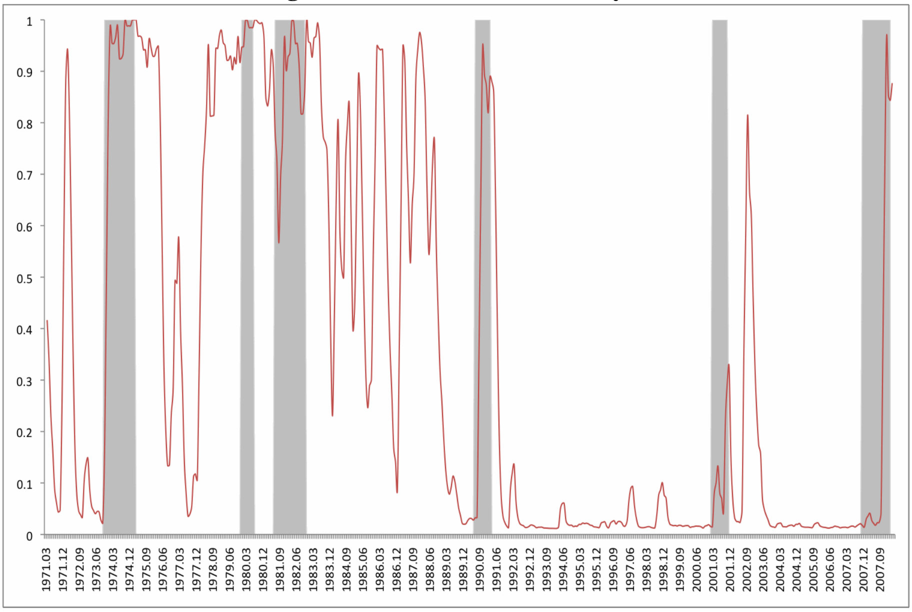


Figure 2.9: Markov Switching Estimation Including a Nominal Discount Rate Dimension

Notes: NBER recession dates in shadowed area. In the upper panel, Regime 1 smoothed probability is plotted, while in the lower panel Regime 2 smoothed probability is plotted.

Regimes 1 Smoothed Probability



Regime 2 Smoothed Probability

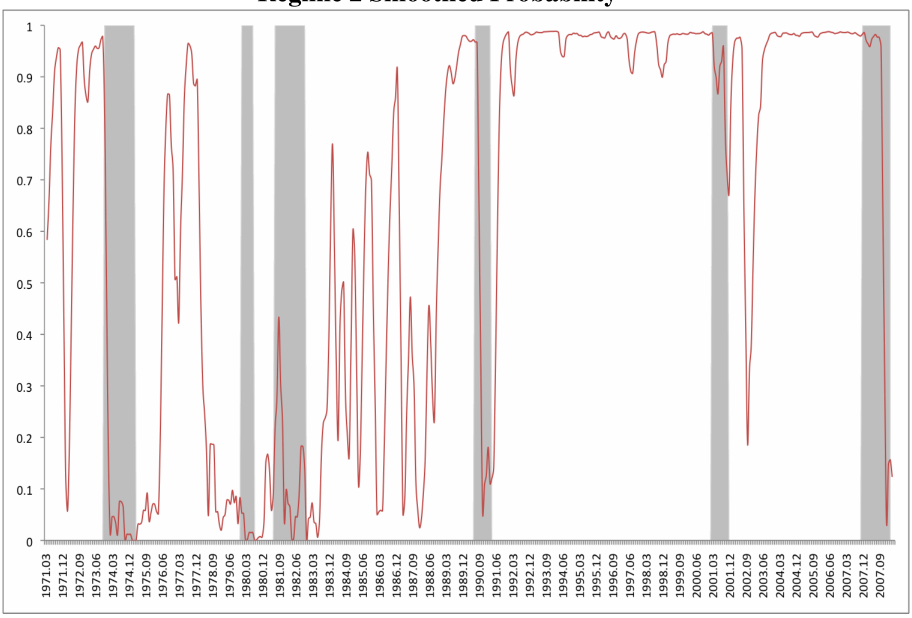
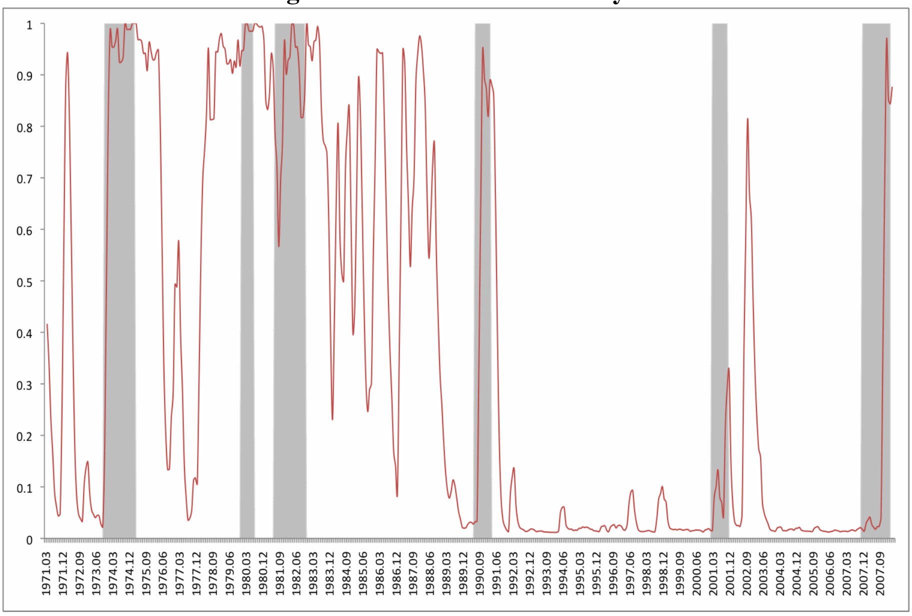


Figure 2.10: Markov Switching Estimation: 1970-2010

Notes: NBER recession dates in shadowed area. Dependent variable is the first difference of the stock yield, where the dividends are smoothed taking the last ten year average: $d\left(\frac{\tilde{D}}{P}\right)_t = \beta_0^{S_t} + \beta_1^{S_t}\pi_t + \beta_2^{S_t} VOL(\pi)_t + \varepsilon_t$. $S_t = 1, 2$ is the state variable which changes through time and cannot be observed by investors. S_t is determined by Markov chain: $Prob\,(S_{t+1} = j \mid S_t = 1) = p_{ji}$. The upper panel of the Figure shows the smoothed probabilities for Regime 1, and the lower panel shows smoothed probabilities for Regime 2.

Regimes 1 Smoothed Probability



Regime 2 Smoothed Probability

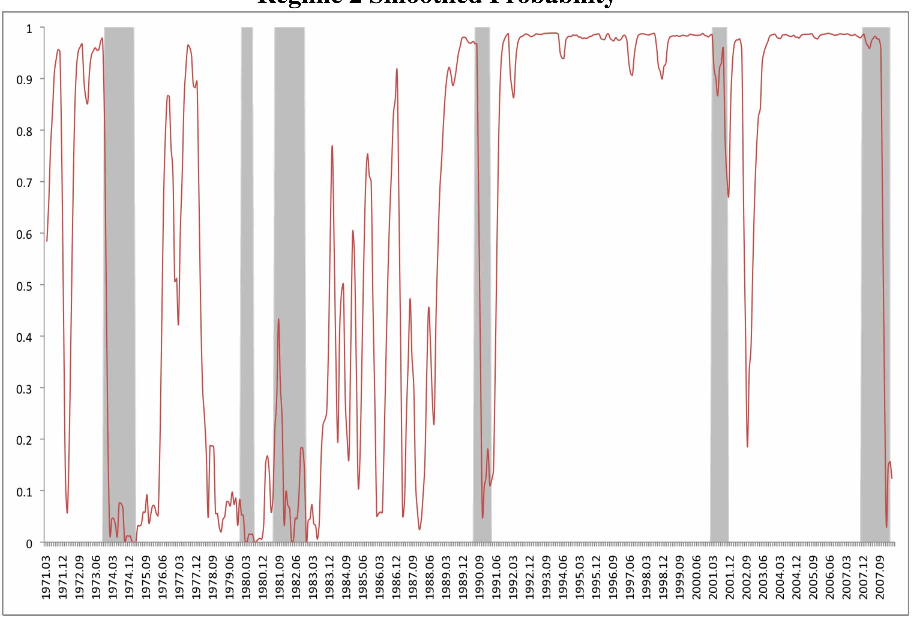


Table 2.1: Rare-Event Probability Estimation

Notes: The table includes the estimated coefficients of a power-law distribution of the form $p(x) = Cx^{-\alpha} \quad for\, x \geq x_m$, following Clauset et al (2009). N is the number of data points for which $x \geq x_m$. The standard deviation of α is calculated as $std\ (\hat{\alpha}) = \frac{\hat{\alpha}-1}{\sqrt{N}}$. The last row shows the probability of observing a month on month inflation increase of al least 10 percent. Note that higher α implies lower probability, but in order to do an acute comparison direct comparison x_m is also relevant. Note that x_m is much higher in the case of the World series (4.14%), while in the cases of USA and Germany is very similar (between 0.8 and 0.95 %). The finite sample bias is not relevant except in the case of Germany (1960), where N is below 50. The World series corresponds to all available monthly inflation data in the IMF IFS database since 1960 (62828 observations).

	USA	**GERMANY (1960)**	**GERMANY (1870)**	**World (1960-2008)**
$\hat{x_m}$	0.0091	0.0107	0.0095	0.0414
N	293	44	200	3923
$\hat{\alpha}$	3.19	3.60	2.17	2.49
std ($\hat{\alpha}$)	0.13	0.39	0.08	0.02
Prob π>10%	0.0005	0.0003	0.0155	0.1113

Table 2.2: Ex-ante Implications

Notes: The Table compares the calibrated stock price when only the probability of the rare event varies. The columns USA(b and c) corresponds to the effect of an increase of 0.001 and 0.002 with respect to the benchmark probability calculated in Table 2. The stock price comes from calibrating the model in Appendix I. For the computations, the following values are used: $\beta = 0.97; f_o = 1.5; \gamma = 2$; $b = 0.9$; $C_o = 2$; and $g = 0.06$. Probability of inflation >10% is calculated as in Table 1.

	USA	**Germany 1870**	**World 1960**	**USA (b)**	**USA (c)**
Prob π >10%	0.0005	0.0155	0.1113	0.0015	0.0025
Stock price	1.2940	1.2770	1.1650	1.2930	1.2920
Diff. benchmark	%	-1.35%	-9.98%	-0.09%	-0.18%
	bps	-135	-998	-9	-18

Table 2.3: Data Description

Notes: Inflation corresponds to month on month variations of the seasonally adjusted CPI. Inflation volatility is the last twelve-month standard deviation of the inflation series. DP_S stands for the trailing dividend price ratio (stock yield) with smoothed dividends (last ten year average of dividends). DP stands for the trailing dividend price ratio (stock yield) with non-smoothed dividends. Finally, the real stock returns figures stand for the S&P 500 monthly return controlling for inflation.

	Inflation	**Inf Volatility**	**DP_S**	**DP**	**Real Stock Return**
January 1970-December 2008					
Mean	0.01108	1.54393	0.03055	0.03102	0.00584
Standard Deviation	0.00831	0.66851	0.01421	0.01291	0.06636
Min	-0.02155	0.36043	0.01074	0.01116	-0.25173
Max	0.03946	3.48940	0.06162	0.06022	0.19810
January 1970-December 1985					
Mean	0.01717	1.50010	0.04562	0.04343	-0.00186
Standard Deviation	0.00884	0.79229	0.00825	0.00876	0.06776
Min	0.00068	0.39193	0.03010	0.02743	-0.20635
Max	0.03946	3.48940	0.06162	0.06022	0.19810
January 1986 - December 2008					
Mean	0.00722	1.57598	0.02090	0.02305	0.01040
Standard Deviation	0.00510	0.58195	0.00708	0.00795	0.06566
Min	-0.02155	0.36043	0.01074	0.01116	-0.25173
Max	0.01727	3.39197	0.03557	0.03791	0.13401

Table 2.4: Markov Switching Estimation: 2 Regimes

Notes: the Table presents the results from a Markov Switching Regime Estimation. Dependent variable is the stock yield (dividend over price ratio). Independent variables are monthy inflation rates (Inflation), and the volatility of monthly inflation rates (Inflation Volatility). The estimated mean, standard deviation and p-values are reported. Regime-1 is associated to weak commitment to low and stable inflation; while Regime-2 is associated to a strong commitment to low and stable inflation. The second panel reports the estimated transition matrix for Regimes 1 and 2. Each column must add up to one. The last two rows of the lower panel reports the expected duration of each regime in number of months.

	Regime-1	**Regime-2**
Constant		
Mean	-0.0008	-0.0004
Std Error (p. value)	0.0004 (0.09)	0.0001 (0.00)
Inflation		
Mean	0.1578	0.0717
Std Error (p. value)	0.0411 (0.00)	0.0149 (0.00)
Inflation Volatility		
Mean	-0.0614	0.0613
Std Error (p. value)	0.1505 (0.68)	0.0389 (0.12)

Estimated Transition Matrix

	Regime-1	**Regime-2**
Regime-1	0.96	0.02
Regime-2	0.04	0.98
Expected Duration Regime-1	24.4	months
Expected Duration Regime-2	41.5	months

Table 2.5: Markov 2 Regime Switching Estimation

Notes:Estimation of Model in Equation . Inflation corresponds to month on month variations of the seasonally adjusted CPI. Inflation volatility is the last twelve-month standard deviation of the inflation series. DP_S stands for the trailing dividend price ratio (stock yield) with smoothed dividends (last ten year average of dividends). D.DP_S stands for the first difference of the DP_S series. DP stands for the trailing dividend price ratio (stock yield) with non-smoothed dividends. Finally, D.DP stands for the first difference of DP series.

		Regime-1			Regime-2		
		CTE	**Inflation**	**Inflation Volatility**	**CTE**	**Inflation**	**Inflation Volatility**
D.DP_S	Value	0	0.16	-0.06	0	0.07	0.06
	Std Error (p. value)	0.0004 (0.09)	0.0411 (0.00)	0.1505 (0.68)	0.0001 (0.00)	0.0149 (0.00)	0.0389 (0.12)
DP_S	Value	0.02	2.29	1.23	0.09	-2.31	-1.23
	Std Error (p. value)	0.0014 (0.00)	0.1857 (0.00)	0.6115 (0.04)	0.7378 (0.90)	18.8737 (0.90)	22.3304 (0.96)
D.DP	Value	0	0.13	-0.13	0	0.05	0.09
	Std Error (p. value)	0.0004 (0.35)	0.0370 (0.00)	0.1354 (0.35)	0.0001 (0.00)	0.0161 (0.00)	0.0395 (0.02)
DP	Value	0.03	1.21	2.68	0.01	-0.01	0.57
	Std Error (p. value)	0.0012 (0.00)	0.1522 (0.00)	0.5207 (0.00)	0.0006 (0.00)	0.0979 (0.92)	0.2209 (0.01)

Table 2.6: Controlling for Expected Economic Growth

Notes: Inflation corresponds to month on month variations of the seasonally adjusted CPI. Inflation volatility is the last twelve-month standard deviation of the inflation series. DP_S stands for the trailing dividend price ratio (stock yield) with smoothed dividends (last ten year average of dividends). DP stands for the trailing dividend price ratio (stock yield) with non-smoothed dividends. Finally, the real stock returns figures stand for the S&P 500 monthly return controlling for inflation.

	(1)		(2)		(3)	
	R1	**R2**	**R1**	**R2**	**R1**	**R2**
Inf	0.206	0.077	0.172	0.077	0.228	0.075
	0.0444 (0.00)	*0.0154 (0.00)*	*0.0417 (0.00)*	*0.0152 (0.00)*	*0.0447 (0.00)*	*0.0154 (0.00)*
Vol			-0.094	0.068	-0.026	0.069
			0.1528 (0.54)	*0.0433 (0.12)*	*0.1527 (0.86)*	*0.0430 (0.11)*
EGDP_2Q	0.0168	0.0006			0.02	0.001
	0.0062 (0.01)	*0.0026 (0.83)*			*0.0062 (0.00)*	*0.0028 (0.82)*
EGDP_4Q-2Q			-0.02	0	-0.03	0
			0.0141 (0.11)	*0.0073 (0.58)*	*0.0137 (0.05)*	*0.0073 (0.53)*

Table 2.7: Controlling for Recessions

Notes: the Table presents the results from a Markov Switching Regime Estimation. Dependent variable is the stock yield (dividend over price ratio). Regime-1 (R1) is associated to weak commitment to low and stable inflation; while Regime-2 (R2) is associated to a strong commitment to low and stable inflation. Inf stands for monthly realized inflation rates; Vol for the volatility of the realized inflation rates defined as the last-12 month standard deviation; EGDP_2Q is the expected real GDP growth rate for next two quarters (from the Livingston Survey). Recession is a dummy variable. The dummy takes the value one when the month is consider as a recession month by the NBER Business Cycle Dating Committee, and zero otherwise. .Standard deviations and p-value in italics. P-value between brackets.

	(1)		**(2)**	
	R1	**R2**	**R1**	**R2**
Inf	0.080	0.100	0.082	0.080
	0.0156 (0.00)	*0.0499 (0.05)*	*0.0530 (0.12)*	*0.0159 (0.00)*
Vol			-0.100	0.051
			0.1865 (0.59)	*0.0399 (0.20)*
Inf . Recession	0.151	0.097	0.142	0.116
	0.0469 (0.00)	*0.0481 (0.05)*	*0.0743 (0.06)*	*0.0599 (0.05)*
Vol . Recession			-0.122	0.113
			0.1978 (0.54)	*0.1005 (0.26)*

Table 2.8: Estimations Using Core Inflation

Notes: Standard deviations and p-value in italics. P-value between brackets. Inf stands for monthly realized inflation rates (excluding food and energy prices); Vol for the volatility of the realized inflation rates defined as the last-12 month standard deviation; EGDP_2Q is the expected real GDP growth rate for next two quarters (from the Livingston Survey); EGDP_4Q-2Q is the expected GDP growth rate for the 12-month-ahead forecast minus the the 6-month-ahead forecast. Recession is a dummy variable. The dummy takes the value one when the month is consider as a recession month by the NBER Business Cycle Dating Committee, and zero otherwise

	(1)		**(2)**		(3)		(4)(		(5)	
	R1	**R2**	**R1**	**R2**	**R1**	**R2**	**R1**	**R2**	**R1**	**R2**
Inf	0.130	-0.012	0.132	-0.012	0.194	0.005	0.059	-0.013	0.001	0.005
	0.0432 (0.00)	*0.0388 (0.76)*	*0.0445 (0.00)*	*0.0326 (0.72)*	*0.0517 (0.00)*	*0.0305 (0.87)*	*0.0513 (0.25)*	*0.0373 (0.72)*	*0.0403(1.00)*	*0.0304 (0.86)*
Vol			-0.056	-0.116	0.085	-0.363			0.2	-0.33
			0.1415 (0.70)	*0.2131 (0.59)*	*0.1542 (0.58)*	*0.0888 (0.00)*			*0.1909 (0.29)*	*0.0673 (0.00)*
EGDP_2Q					0.02	0.001				
					0.0061 (0.00)	*0.0027 (0.60)*				
EGDP_4Q-2Q					-0.02	-0.01				
					0.0137 (0.11)	*0.0066 (0.35)*				
Inf . Recession							0.094	0.090	0.191	0.139
							0.0446 (0.03)	*0.0657 (0.17)*	*0.0648 (0.00)*	*0.0724 (0.06)*
Vol . Recession									-0.381	-0.219
									0.2281 (0.10)	*0.1279 (0.09)*

Table 2.9: Estimations Using Non-Energy Inflation

Notes: the Table presents the results from a Markov Switching Regime Estimation. Dependent variable is the stock yield (dividend over price ratio). Regime-1 (R1) is associated to weak commitment to low and stable inflation; while Regime-2 (R2) is associated to a strong commitment to low and stable inflation. Inf stands for monthly realized inflation rates (excluding energy prices); Vol for the volatility of the realized inflation rates defined as the last-12 month standard deviation; EGDP_2Q is the expected real GDP growth rate for next two quarters (from the Livingston Survey); EGDP_4Q-2Q is the expected GDP growth rate for the 12-month-ahead forecast minus the the 6-month-ahead forecast. Standard deviations and p-value in italics. P-value between brackets.

	(1)		**(2)**		**(3)**	
	R1	**R2**	**R1**	**R2**	**R1**	**R2**
Inf	0.159	0.083	0.153	0.052	0.235	0.058
	0.0514 (0.00)	*0.0232 (0.00)*	*0.0523 (0.00)*	*0.0313 (0.10)*	*0.0583 (0.00)*	*0.0320 (0.07)*
Vol			0.081	0.163	0.099	0.134
			0.1572 (0.61)	*0.1128 (0.15)*	*0.1698 (0.56)*	*0.1118 (0.23)*
EGDP_2Q					0.02	0.000
					0.0067 (0.01)	*0.0020 (0.96)*
EGDP_4Q-2Q					-0.03	0
					0.0154 (0.06)	*0.0078 (0.54)*

Table 2.10: Markov Switching Estimation: Germany 1970-2010

Notes: the Table presents the results from a Markov Switching Regime Estimation. Dependent variable is the stock yield (dividend over price ratio). Independent variables are monthy inflation rates (Inflation), and the volatility of monthly inflation rates (Inflation Volatility). The estimated mean, standard deviation and p-values are reported. Regime A is associated to a strong commitment to low and stable inflation, while Regime B is associated to weak commitment to low and stable inflation. The second panel reports the estimated transition matrix for Regimes 1 and 2. Each column must add up to one. The last two rows of the lower panel reports the expected duration of each regime in number of months. Note that the only significant regime is Regime A.

	Regime A	**Regime B**
Constant		
Mean	0.0371	-0.0370
Std Error (p. value)	0.00001 (0.001)	0.00001 (0.001)
Inflation		
Mean	0.05170	-0.05809
Std Error (p. value)	0.00001 (0.001)	0.00002 (0.001)
Inflation Volatility		
Mean	-0.12224	0.12665
Std Error (p. value)	0.00001 (0.001)	0.00002 (0.001)

Estimated Transition Matrix

	Regime A	**Regime B**
Regime A	1	1
Regime B	0	0
Expected Duration Regime-1	Infinite	months
Expected Duration Regime-2	0	months

Table 2.11: Markov Switching Estimation Including a Nominal Discount Rate Dimension

Notes: Standard deviations and p-value in italics. P-value between brackets. Inf stands for monthly realized inflation rates; Vol for the volatility of the realized inflation rates defined as the last-12 month standard deviation; PC_1 is the first principal component of the Investment Opportunity Set; EGDP_2Q is the expected real GDP growth rate for next two quarters (from the Livingston Survey); EGDP_4Q-2Q is the expected GDP growth rate for the 12-month-ahead forecast minus the the 6-month-ahead forecast.

	(1)		**(2)**		**(3)**		**(4)**	
	R1	**R2**	**R1**	**R2**	**R1**	**R2**	**R1**	**R2**
Inf	0.14	0.09	0.14	0.08	0.16	0.08	0.21	0.08
	0.0429 (0.00)	*0.0154 (0.00)*	*0.0427 (0.00)*	*0.0154 (0.00)*	*0.0443 (0.00)*	*0.0156 (0.00)*	*0.0448 (0.00)*	*0.0158 (0.00)*
Vol			-0.08	0.05	-0.10	0.06	-0.03	0.06
			0.1537 (0.59)	*0.0397 (0.22)*	*0.1523 (0.50)*	*0.0430 (0.16)*	*0.1432 (0.83)*	*0.0426 (0.14)*
PC_1	0.00290	-0.00130	0.00290	-0.00110	0.00230	-0.00110	0.00330	-0.00120
	0.0015 (0.06)	*0.0007 (0.06)*	*0.0015 (0.05)*	*0.0006 (0.08)*	*0.0016 (0.15)*	*0.0007 (0.09)*	*0.0015 (0.03)*	*0.0006 (0.07)*
EGDP_4Q-2Q					-0.02	-0.01	-0.02	-0.01
					0.0144 (0.27)	*0.0072 (0.48)*	*0.0133 (0.16)*	*0.0069 (0.35)*
EGDP_2Q							0.0002	0.0001
							0.0001 (0.00)	*0.0001 (0.88)*

Table 2.12: Markov Switching Estimation: 1970-2010

Notes: the Table presents the results from a Markov Switching Regime Estimation. Dependent variable is the stock yield (dividend over price ratio). Independent variables are monthy inflation rates (Inflation), and the volatility of monthly inflation rates (Inflation Volatility). The estimated mean, standard deviation and p-values are reported. Regime-1 is associated to weak commitment to low and stable inflation; while Regime-2 is associated to a strong commitment to low and stable inflation. The second panel reports the estimated transition matrix for Regimes 1 and 2. Each column must add up to one. The last two rows of the lower panel reports the expected duration of each regime in number of months.

	Regime-1	**Regime-2**
Constant		
Mean	-0.0009	-0.0004
Std Error (p. value)	0.0004 (0.04)	0.0001 (0.00)
Inflation		
Mean	0.086	0.0817
Std Error (p. value)	0.0375 (0.02)	0.0151 (0.00)
Inflation Volatility		
Mean	0.1901	0.0657
Std Error (p. value)	0.1216 (0.12)	0.0394 (0.10)

Estimated Transition Matrix

	Regime-1	**Regime-2**
Regime-1	0.97	0.04
Regime-2	0.03	0.96
Expected Duration Regime-1	34.39	months
Expected Duration Regime-2	22.54	months

3 INFLATION, UNCERTAINTY AND PRICE OF RISK: LET DATA SPEAK FOR ITSELF

3.1 INTRODUCTION

Does inflation increase the price of risk? It has been suggested that the negative correlation between real stock prices and inflation is explained by a positive relation between inflation and risk. For example, Brandt and Wang (2003) assume that relative risk aversion depends on shocks to inflation rates. Bekaert and Engstrom (2010a) show that expected inflation correlates positively with risk aversion and uncertainty. While of these results stress the relevance of the 'inflation-uncertainty' relation and the 'inflation-price of risk' relation, no study has delved into these relationships using cross-country macroeconomic data.

In this paper, I test whether macroeconomic data provide evidence for a positive relation between inflation and uncertainty, and between inflation and the price of risk (i.e. relative risk aversion). I work with a sample of forty-three countries, of which eight are considered Developed countries, eleven European countries (European countries not included as Developed) and twenty-four Emerging countries. The different subsamples are constructed so to control for different degrees of financial development.

First, the relationship between inflation and uncertainty is tested. Following Fischer et al. (2002), I work with different inflation ranges. For each of the ranges, I find the empirical distribution of real consumption growth rates and the distribution of real stock returns. Two measures of uncertainty are used: the regime-conditional standard deviation for real consumption growth rates and for real stock returns. The exercise is performed for Developed, European and Emerging countries, and I check whether the assumed positive and monotonic relation between inflation and uncertainty holds in all inflation ranges.

Second, to test the relation between inflation and the price of risk, I follow Campbell (2003) in estimating the implicit values of relative risk aversion for different inflation ranges (regimes). Doing so, I control for uncertainty on both consumption growth rates and real returns. For each regime, I simulate expected returns, using transition probability matrices for inflation regimes, as well as the actual regime-conditional distributions[1] for real stock returns. For the regime-conditional moments for consumption growth rates, I calibrate the Euler condition under both power utility and Epstein-Zin-Weil preferences, so to get the implicit risk aversion coefficient per regime.

Finally, I test whether the cross-country macroeconomic data support the stagflation risk premium approach developed in Chapter 2 of this dissertation. The explanation builds on Rietz (1988) and Barro (2005, 2009) macro-disaster risk, where the disasters are connected to stagflation episodes. Stagflations are long duration events, during which nominal stock prices show a downward trend, while inflation tends to be high[2]. During these periods, real stock prices may decrease up to 90 percent from peak to trough (e.g. the Spanish stock market from 1973 to 1982). For the average stagflation episode, the decrease in nominal stock prices explain less than 8 percent of the cumulative fall in real terms, while inflation explains more than 92 percent. Stagflation episodes may end up in hyperinflation episodes. In this paper, I test if higher inflation rates increase the risk of suffering strong losses in the stock market (i.e. real stock price collapse). I simulate different real stock price paths, conditional on the initial in-

[1] I also work under the assumption of real returns following Normal and Log-Normal distribution.

[2] For stagflation episodes, it is not necessary for inflation to follow an upward trend for the whole episode. In most cases, stagflation episodes start with a strong positive inflation trend, which later stabilizes or even present a downward trend. See Section 5 for a discussion on stagflation episodes.

flation range, and find the probability of real stock prices falling more than 50 percent from peak to trough.

Regarding the inflation and uncertainty relationship, the results show that there is a strong relation between inflation and uncertainty, but only for inflation levels above 10 percent (annualized rates). For inflation below that threshold, there is not clear evidence on a positive 'inflation-uncertainty' relation. When inflation rates are in the 0-10 percentage range, average consumption growth rates do not show a declining trend. The same is true for the volatility of real consumption growth rates. However, for inflation levels above 10 percent, consumption growth rates decline while volatility increases. Working with real stock returns tells a similar story. The main difference is that, when inflation is in the 0-10 percentage range, realized average real stock returns decrease with inflation. However, there is not a robust trend for volatility in that inflation range. For inflation ranges above 10 percent, real returns decrease as volatility increases.

On the inflation and risk price (relative risk aversion) relationship, again it is present only in some inflation ranges. When using all the countries available in the sample, the positive relation between inflation and relative risk aversion is present for inflation ranges between 10 and 50 percent. For lower inflation regimes, the positive relation is not robust. Moreover, for inflation rates above 50 percent, risk aversion decreases. The results are robust to power utility and Epstein-Zin-Weil preferences (see Smith 1999).

The probability of suffering a real stock price collapse increases monotonically with inflation. The simulations show that the conditional probability of experiencing a real stock price collapse (defined as a fall higher than fifty percent from peak to trough in a ten year period) increases in the inflation range for all countries in the sample, as well as for Developed, European and Emerging country subsamples. Therefore, while both the inflation-uncertainty and the inflation-risk aversion relationships are not robust for inflation rates in the 0 to 10 percent inflation range, the probability of suffering a real stock price collapse increases in all inflation ranges, in a monotonic way, and for all the subsamples (Developed, European and Emerging countries). Quantitatively, for inflation rates in the 0-3 percentage range, the probability of a collapse in real stock prices is 0.0029 for Developed countries, 0.047 for European countries and 0.222 for Emerging countries. For the pooled sample, the probability is 0.032. For inflation rates in the 5-10 percentage range, the probability of a collapse in real stock prices is 0.0032 for Developed countries, 0.052 for European countries and 0.261 for Emerging countries. For the pooled sample, the probability is 0.041.

When trying to explain the negative relation between inflation and real stock prices, the literature has recently emphasized the relevance of the 'inflation-uncertainty' relation and the 'inflation-price of risk' relation. Brandt and Wang (2003) test a consumption-based asset pricing model in which risk aversion is time-varying and depends on shocks to both consumption growth and inflation. They give a set of potential reasons why time varying risk aversion should depend on unexpected inflation, but no explanation is conclusive. On the empirical side, Bekaert and Engstrom (2010b) show that expected inflation correlates positively with risk aversion and uncertainty. They build a habit-based measure of risk aversion, and show the positive relation is robust for the period 1970-2010. As a measure of uncertainty, they use the standard deviation of GDP growth forecasts. The positive relation between inflation and risk (both quantity and price of risk) explains more than seventy-five percent of the covariance between inflation and stock yields. However, there is no explanation on why risk aversion may depend on inflation. Pereira (2010), working with a sample of Emerging Markets, finds that close to twenty percent of the positive covariance between inflation and earning yields is explained by falling expected real earning growth rates. The other eighty percent is explained by an increase in risk. The author neither tests directly the relation between inflation and risk, nor disentangles between risk quantity and risk price.

This paper is structured in the following way. Section 2 describes the data sample, the inflation regimes and transition probability matrices for different inflation ranges. Section 3 discusses the evidence on the relation between inflation and uncertainty. In Section 4, I discuss the evidence on the relation between inflation and the price of risk (i.e. the relative risk aversion coefficient). In Section 5, I introduce stagflation episodes as macroeconomic disasters, and discuss whether the probability of a real stock price collapse increases with inflation levels. Section 6 concludes.

3.2 Data

I work with 43 countries, of which eight are Developed countries, eleven are European countries (those European countries not included in the Developed sample), and the rest Emerging countries (including Russia). I work with the three subsamples, as well as with the complete pooled sample. Table 3.1 presents the country sample used in this study.

For these countries, the series for both inflation rates and real returns are constructed for the period 1960 to 2010, at a quarterly frequency. For the inflation growth rates, I first adjust the CPI series for seasonality, and then construct the quarter on quarter rates. For real returns series, I deflate the nominal stock market index using the CPI series, and then construct the quarter on quarter real returns. Annualized inflation rates and real stock returns are used in this paper. The data is from IMF IFS database and Global Financial Database.

Real consumption growth rates are constructed from the Penn World Tables, version 7.0. The figures are on annual basis. I construct real consumption series by multiplying the real GDP per capita (RGDPL) times the Consumption Share of Real GDP per capita (KC).

3.2.1 Inflation Regimes

To understand the relation between inflation and stock returns, I follow a similar strategy to Fischer et al. (2002). Different regimes are defined by ranges of inflation rates. I work with eight regimes, defined just by taking into account annualized inflation rate. The first regime is for inflation below zero (deflation regime). Seven regimes correspond to positive inflation rates: Regime 2 for inflation between 0 and 3 percent; Regime 3 for inflation between 3 and 5 percent; Regime 4 for inflation between 5 and 10 percent; Regime 5 for inflation between 10 and 25 percent; Regime 6 for inflation between 25 and 50 percent; Regime 7 for inflation between 50 and 75 percent; and finally, Regime 8 for inflation rates above 75 percent.

I use these different inflation ranges to test how uncertainty relates to inflation. I work with uncertainty both in real consumption growth rates and in real stock returns. Conditional on the regimes, I first report the distribution of real returns, and second, the moments for real consumption growth rates.

3.2.2 Transition Probability Matrices

Once regimes are defined, I estimate the probability of changing regimes in the subsequent period. I present the transition probability matrices for the different samples In Table 3.3. As in Fischer et al. (2002), each matrix is categorized by the (annualized) inflation rate in year t (rows), and shows the probability of observing the (annualized) inflation rate in the subsequent year (t+1) in a different range. The matrices are built using quarterly data. To understand better the transition matrix, let me explain the results when using the pooled sample. The actual inflation ranges are in the rows. Row one corresponds to Regime 1 (inflation rates below 0) in year t. The transition probability matrix is reporting that the probability of observing inflation in the 0-3 percentage range in the subsequent year is 0.1068 (entry corresponding to row 1, column 1), while the probability of observing inflation in the 3-5 percentage range in the next year is 0.2657 (entry corresponding to row 1, column 2). Note that the sum of probabilities per row equals one.

Note that both the matrix for Developed and for European countries do not show probabilities for Regimes 7 and 8. The reason is that there are no observations in these ranges in the period 1960-2010. The first interesting fact is that inflation in most of the periods is between 0 and 10 percent. Second, deflation periods tend to have a short duration, as the probability of observing positive inflation rates in the subsequent year is close to 0.9. However, the unconditional probability of experiencing a deflation period is higher for Developed countries. Third, on high inflation episodes, these are also short-lived. Once inflation reaches the 25-50 percentage inflation range, the probability of observing again inflation rates in that range in the subsequent year is very small (0.016 for Developed and 0.009 for European countries).

When working with Emerging Countries, the picture is different. First, there are observations in Regimes 7 and 8, that is, for inflation rates above 50 percent. Second, inflation in most of the periods is between 3 and 25 percent. Third, while it is still true that deflation periods tend to have a short duration, the unconditional probability of a deflation episode is the highest of all subsamples. Finally, extreme inflation regimes, defined in this exercise for inflation rates above 50 percent, present a long expected duration. Note that the probability of observing inflation above 50 percent if today inflation rate is between 50 and 75 percent is 0.34. More extreme is the case for inflation levels above 75 percent, as the probability to remain in that range is 0.47. Most of the inertia in the extreme inflation ranges are explained by the long inflationary periods experienced by Latin American countries in the 60s, 70s and 80s.

When working with all the countries available in the sample, three features of the transition probability matrix are noteworthy. First, inflation in most of the periods is between 0 and 10 percent. Second, deflation periods tend to have a short duration, as the probability of observing positive inflation rates in the subsequent year is close to 0.9. Third, extreme inflation regimes, defined in this exercise for inflation rates above 50 percent, present a long expected duration. Note that the probability of observing inflation above 50 percent if today inflation rate is between 50 and 75 percent is 0.26. More extreme is the case for inflation levels above 75 percent, as the probability to remain in that range is 0.46. These last two cases strictly follow to the Emerging Market behavior.

3.3 Inflation and Uncertainty

It is commonly assumed that inflation is positively related to uncertainty. I use the macroeconomic data introduced above to test if this assumption is robust to different inflaton rate levels. To measure uncertainty I use the volatility of real consumption growth rates and the actual distribution of real stock returns per Regime.

3.3.1 Regime-Conditional Real Consumption Growth Rates Distribution

The results for the 'inflation-uncertainty' relationship when using real consumption growth rates are reported in Table 3.4. When working only with Developed markets the 'inflation-uncertainty' relation is weak. Regime 1 (deflation) is the state that presents the lowest average consumption growth rates, though positive, averaging 1.9 percent annually. The mean consumption growth rates peaks in the interval 5-10 percentage, with an average consumption growth rate of 3.0 percent. For higher inflation ranges, consumption rates decrease, having the minimum average rate in the 25-50 percentage interval, with a 2.35 percent variation.

The path for volatility is different from expected, as there is no clear trend as inflation ranges increase. The minimum standard deviation is for Regime 1 (deflation). Although it is true that volatility increases as inflation rates become positive, volatility in Regime 5 is lower than in Regime 4, which at a time is lower than volatility in Regime 3. Therefore, when inflation is in the 5 to 25 percent range, volatility of consumption growth rates seem to decrease. In Regime 6, volatility jumps, increasing more than 100 percent with respect to volatility in Regime 5.

The case for European countries is very similar to the Developed country one. First, the minimum consumption growth rate takes place in Regime 1 (deflation). Second, for positive inflation ranges there is a negative trend for growth rates, although the average consumption growth rate in Regime 6 is slightly higher than in Regime 5. With respect to consumption growth rates volatility, the minimum standard deviation is for Regime 1 (deflation), as in the case of Developed countries. Second, volatility increases as inflation rates become positive, peaking in Regime 6. However, volatility in Regime 3 is higher than in Regimes 4 and 5. Again, there is not a robust relation between inflation levels and uncertainty.

The Emerging Market subsample presents the peak of growth rates in again in Regime 1. In this case, since inflation in Emerging countries reach figures above 75 percent, the maximum effect of inflation on consumption growth rates takes place in Regime 8. The average consumption growth rate is -0.09 in this range. From Regime 3 on, there is a strong downward trend for consumption growth rates. On the other side, volatility does not increase as expected in the 3 to 25 percent range. Note that volatility in Regimes 4 and 5 are both lower than in Regime 3. However, from Regime 6 on, the standard deviation of conditional regime consumption growth rates increases strongly.

Working with the complete sample does not change the results qualitatively. For average consumption growth rates, the global peak takes place in Regime 1. For positive inflation ranges, the peak in Regime 3 (3-5 percentage inflation range). From Regime 3 on, consumption rates decrease as inflation increases. Uncertainty does increase from Regime 5. However, it is still true that volatility in Regime 4 is lower than in Regime 3. That is, for inflation rates between 0 and 10 percent, there is no monotonic relation between inflation and uncertainty.

3.3.2 Regime-Conditional Return Distribution

In Table 3.5 the moments for the conditional real return distributions are presented. In Panel A, the results for developed countries are introduced; Panel B presents the results for European countries (not included as Developed countries), Panel C for Emerging countries; and finally Panel D for all countries in the sample.

For Developed countries, real returns decrease with inflation ranges, volatility increases, and the average loss in the high inflation ranges is higher than the loss when deflation episodes. Starting with Regime 1, that is, when inflation rates are negative, the real return average (on annual basis) is -0.0248. A negative return for deflation periods, which is characteristic of recession periods driving inflation downwards as aggregate demand decreases. Moreover, the volatility in this regime is the highest for developed countries, 0.1991. For positive inflation rates, real returns become positive, peaking in Regime 2 (inflation in the 0 to 3 percent range). For Regimes 3 and 4 the average return decreases. However, note that volatility does not increase as expected. In fact, the volatility in Regime 4 is lower than in Regime 3. For higher inflation ranges, Regimes 5 and 6, returns are negative, and the data shows a strong -0.0815 in Regime 5 and -0.1717 in Regime 6. As expected, volatility jumps in Regimes 5 and 6 when compared to Regimes 2-4. Volatility increases on average a 32 percent (average volatility of Regimes 5-6 over average volatility of Regimes 2-4).

The case for European Countries (not included as developed) is similar to Developed country case: real returns decrease for higher inflation ranges, but there is not a clear positive relation between volatility and inflation ranges. Main difference is that the deflation regime shows positive average return, 0.032. However, volatility peaks in this range. For positive inflation ranges, it is still true that the average return decreases as inflation increases. Noteworthy, real returns decrease heavily in Regime 6, -0.392 compared to -0.1717 for the Developed Country sample. A puzzling result is that the volatility in Regime 6 is lowest among the six inflation ranges.

Working with Emerging countries does not change the main conclusions. Real returns decrease as inflation level increases, and volatility increases. In this case, the relation between average real returns and inflation ranges is monotonic (exception for Regime 7). The relation between volatility and inflation ranges is monotonic from Regime 2 on. The maximum average return takes place in Regime 1 (negative inflation rates), and the minimum in Regime 8, -0.063. The average return in regime 7 is unexpected, as the figure is higher than the return in the previous inflation range (-0.0184 compared to -0.0374). The high inflationary inertia experienced by Latin American countries in the 60s and 70s may explain these results. During that period, most countries experienced annual inflation rates close to 60 percent. Some countries ended in hyperinflation episodes (Brazil, Argentina), but most of them were able to avoid that scenario.

The last panel in Table 3.5 reports the results when pooling all the countries in the sample. First, average real returns decrease from

Regime 2 on, except for Regime 7. Second, volatility increases with inflation from Regime 4. For regimes 2 to 4 (inflation between 0 and 10 percent), there is not significant relation between inflation and volatility. Regarding the first result, the exception in Regime 7 may be explained by Latin American countries, as discussed above. About the second result, note that volatility for Regimes 2 to 4 slightly varies, being 0.2101 for Regime 2, 0.1998 for Regime 3, and 0.2182 for Regime 3. In other words, when inflation is in the 0 to 10 percent range, volatility of real returns does not show a clear trend.

To conclude this section on inflation and uncertainty, using two of the most used measures of uncertainty, the standard deviation of consumption growth rates and the standard deviation of real stock returns, data for the period 1960-2010 suggest that there is a strong relation between inflation and uncertainty, but only for inflation levels above 10 percent (on an annual basis). For inflation below that threshold, there is no clear evidence indicating a positive relation.

3.4 Inflation and Price of Risk

After studying the relation between inflation and the quantity of risk (uncertainty), in this section I analyze the relation between inflation and the price of risk. I use the coefficient of relative risk aversion (RRA) as the price of risk. To find the RRA coefficient per inflation range, I first simulate expected returns when the initial state corresponds to different inflation ranges. Then, I plug the expected real returns in the Euler condition for a power utility and Epstein-Zin-Weil utility, and test whether the implicit coefficients of risk aversion changes with the inflation range.

3.4.1 Simulation of Regime-Conditional Expected Returns

In order to estimate the regime conditional relative risk aversion coefficient, I use the estimated transition probability matrices and simulate the stock expected return conditional on the initial regime. That is, the expected return when the initial period $t_0 \, \varepsilon \, R_j$ for $j = 1, 2, ..., 8$. For regime-switching models, the distribution of the expected returns depends on the starting regime. I simulate different patterns conditional on initial value belonging to each regime interval. For Regime J, a random realization for the stock real return is picked coming from: (i) the *Normal* $\left(\mu_J, \sigma_J^2\right)$ distribution; and, (ii) the actual real return distribution conditional on the inflation rate belonging to Regime J interval[3]. For the simulation algorithm under Markov Switching regime see Hardy (2003).

When performing classic Brownian motion simulations markets are complete, so there a unique martingale measure exists. However, if Markov switching regimes is allowed the variance becomes stochastic and the markets are not complete anymore. Simulating the stock prices becomes a non straightforward exercise, since the there is not a unique equivalent probability measure, thus no unique prices for the stock in the simulated period realizations. To find such a probability measure, I use the Esscher transformation (Esscher (1932)). The Esscher transformation is used in actuarial finance. Some papers using this transformation are Gerber and Shiu (1994); Webb (2003)and Piaskowski (2005), in all cases for option pricing purposes. The Esscher transformation works on the transition probabilities. The Esscher transitional probabilities are defined as:

$$p_{ij}^{(h)} = Pr\left(h, z_t = j \mid z_{t-1} = i\right) = \frac{p_{ji}\, exp\left\{h_i \left[\mu_j - 0.5\sigma_j^2\right]\tau + 0.5\sigma_j^2 \tau h_i\right\}}{\sum_{j=1}^{M} p_{ji}\, exp\left\{h_i \left[\mu_j - 0.5\sigma_j^2\right]\tau + 0.5\sigma_j^2 \tau h_i\right\}}$$

[3]I also work with LogNormal distributions, *LogNormal* $\left(\mu_j, \sigma_j^2\right)$, where $j = 1, 2, ..., 8$, both the mean and the volatility are Regime dependent. The results are not reported since they do not add relevant information when compared to the two distributions discussed.

The Esscher parameter vector h is computed numerically solving the following conditions:

$$\sum_{j=1}^{M} p_{ji}\, exp\left\{h_i\left[\mu_j - 0.5\sigma_j^2\right]\tau + 0.5\sigma_j^2\tau h_i\right\}\left(exp\left\{\mu_j\tau + \sigma_j^2\tau h_i\right\} - exp\left\{r\tau\right\}\right) = 0$$

being h_i an unique point in the interval $\left(\min_j\left(\frac{r-\mu_j}{\sigma_j^2}\right), \max_j\left(\frac{r-\mu_j}{\sigma_j^2}\right)\right)$. Simulations are performed for Developed, European, and Emerging countries, and for all the countries in the sample (pooled sample). I use the transition probability matrices for the four cases, and use the moments and distributions of real returns, as described in the previous section. The procedure is repeated a 1,000,000 times.

The results from the estimations are presented in Table 3.6. I report only the simulations when working with Normal distributions and the actual distributions. Starting with the Developed countries and assuming Normal distributions, the simulations show that returns fall conditional on the initial state. When the initial state is a deflationary regime (Regime 1) the mean return is slightly negative (-0.14 percent). Conditional on the initial period being in Regime 2, the return jumps considerably to 4.45 percent. However, if the initial state corresponds to inflation belonging to the interval 3-5 percentage, then the average simulated return decreases to 1.47 percent. Simulated returns become negative conditional on the initial state being Regime 5 or 6, that is, for inflation above ten percent. For Regime 5 the simulated return is -7.07 percent while for Regime 6 the return is a little bit higher -4.69 percent.

The results vary when working with the actual regime-conditional real return distributions. In this case, conditional on starting in a deflationary state, the average return is a positive 3.6 percent. For Regime 2, the average real return becomes 3.5 percent, while conditional on initial state being Regime 3 the return decreases to 3.3 percent. Significant falls take place when conditioning the initial state to be in Regimes 4, 5, and 6: 2.7, 1.4, and 0.9 percent, respectively. The higher the initial inflation regime, the lower the simulated annual returns.

For the European countries sample (those countries not included as developed), the results present some variations. First, the returns are higher. Second, only for the simulations starting in Regime 6 we find negative returns (and only if working with actual regime distributions). When the initial state is in a deflationary regime, the simulated return is 9.64 percent, much higher than the developed countries return. The simulated return decreases monotonically with the conditional initial Regime: 9.5, 7.9, 5.4, and 0.9 percent for Regimes 2, 3, 4 and 5, respectively. Finally, for Regime 6 the simulated return is negative (-0.61 percent).

The negative relation between the initial regime (actual inflation range) and simulated returns is also present in the case of Emerging Markets. If the initial state corresponds to the deflation regime (Regime1), the simulated annual return is an impressive high 21.57 percent. The return slightly increases if the initial state corresponds to Regime 1 range to 22.52 percent. When the initial state is for the 3-5 percentage inflation range, then the simulated return decreases to 20.35. The return keeps decreasing monotonically with the initial inflation range: 19.1 percent (Regime 4); 14.1 percent (Regime 5), 6.7 percent (Regime 6), -7.3 percent (Regime 7), and finally -18.0 percent in Regime 8.

Finally, I work with all the countries in the sample, without making distinction between developed and developing markets. When working with the actual regime-conditional distribution for real returns, the simulated annual returns are monotonically decreasing with the initial inflation range for positive inflation figures (from Regime 2 onwards). If the initial state corresponds to the deflation regime

(Regime 1), the simulated annual return is 11.9 percent. It increases when the initial state corresponds to the 0-3 percentage inflation range to 13.6 percent, and then decreases for higher inflation ranges: 11.0 percent (Regime 3), 9.4 percent (Regime 4), 4.9 percent (Regime 5), -1.9 percent (Regime 6), -12.8 percent (Regime 7), and finally -20.8 percent (Regime 8).

The main conclusion is that, independent of the sample used for the simulations, in all cases the higher the initial inflation range state, the lower the simulated annual real returns for stocks. This conclusion reinforces the negative correlation between realized (or expected inflation) and real stock prices (or returns) discussed in the literature. In the next section I use the results in this section and the previous ones to test whether this negative correlation is only explained by uncertainty increase or by both an increase in uncertainty and risk aversion (both the quantity and price of risk).

3.4.2 Regime-Implicit Relative Risk Aversion (RRA) Coefficient

3.4.2.1 Power Utility

To estimate the conditional relative risk aversion coefficient I follow the same theoretical setup as in Campbell (2003), working with the Consumption Capital Asset Pricing Model (C-CAPM). I assume a representative investor who faces an inter-temporal choice problem in complete and frictionless capital markets. The representative investor maximizes a time-separable utility function, $U(c_t)$, in consumption c_t. The solution to this problem yields the following Euler condition:

$$U^{'}(c_t) = \delta E_t\left[(1+R_{t+1})U^{'}(c_{t+1})\right]$$

where δ is the discount factor and $(1+R_{t+1})$ represents the gross rate of return. Employing a time-separable power utility function

$U\left(c_t\right)=\sum \delta^j \frac{c_{t+j}^{1-\gamma}}{1-\gamma}$ where γ is the relative risk aversion (RRA) coefficient. Substituting the utility function in the Euler condition the condition becomes

$$1=E_t\left[\left(1+R_{t+1}\right)\delta\left(\frac{c_{t+1}}{c_t}\right)^{-\gamma}\right]$$

As in Hansen and Singleton (1983), the condition can be expressed as

$$E_t\left(r_{t+1}\right)+log\left(\delta\right)-\gamma E_t\left(\triangle c_{t+1}\right)+0.5\left(\sigma_r^2+\gamma^2\sigma_c^2-2\gamma\sigma_{rc}\right)=0$$

To find the Regime dependent risk aversion coefficient I follow a dual strategy. First, I find the coefficient of relative risk aversion that is solution for Equation 3 in each Regime. For each asset class (developed, European, emerging and complete sample stocks), I have the consumption growth first and second moments and the first and second moments for real returns under the regime-specific expectation space. These last set of parameters come from the simulation exercises discussed in the previous section. The only parameter that needs to be assumed is the covariance between consumption and real return innovations, σ_{rc}. I work with different values for the correlation of consumption and real return innovations, since $\sigma_{rc}\rho_{rc}=\sigma_r\sigma_c$.

Second, using the previous equation, it must be the case that

$$E_t^{s=K}\left(r_{t+1}\right)-\gamma_{s=K}E_t^{s=K}\left(\triangle c_{t+1}\right)+0.5\left(\sigma_{r,s=K}^2+\gamma_{s=K}^2\sigma_{c,s=K}^2-2\gamma_{s=K}\sigma_{rc,s=K}\right)=$$
$$E_t^{s=l}\left(r_{t+1}\right)-\gamma_{s=L}E_t^{s=L}\left(\triangle c_{t+1}\right)+0.5\left(\sigma_{r,s=L}^2+\gamma_{s=L}^2\sigma_{c,s=L}^2-2\gamma_{s=L}\sigma_{rc,s=L}\right)$$

for any Regimes K and L. Under the assumption of a linear relation between the conditional risk aversion coefficients, that is, $\frac{\gamma_{s=L}}{\gamma_{s=K}}=Constant$. Substituting in the expression, and taking $\gamma_{s=L}$ as given, I find the constant which solves the expression for different values of the Kth regime, $K\neq L$.

Table 3.7 reports the results of the first procedure when working with the pooled sample. The relative risk aversion coefficients when the initial state belongs to 0-3 percentage inflation range is between 8.9 (when the correlation between consumption and real return innovations, ρ_{rc}, is 0), and 8.6 ($\rho_{rc} = 1$). Some comments on the results are worth. First, the risk aversion coefficient decreases when the correlation between consumption and real return innovations increases. Second, in all cases the risk aversion coefficient is below 10, in line with the upper bound for the coefficient as discussed in Gollier and Schlesinger (2002).

When the initial state belongs to 3-5 percentage inflation range, the relative risk aversion coefficient is between 8.1 ($\rho_{rc} = 0$) and 7.6 ($\rho_{rc} = 1$). As before, the relative risk aversion is lower than 10, and decreases with ρ_{rc}. More importantly, for all correlations between consumption and real return innovations, the risk aversion coefficient is lower than for the 0-3 percent inflation regime. The results for the 5-10 percentage inflation range, are very similar to the 3-5 range.

However, the relative risk aversion starts to increase significantly when inflation is higher than 10 percent. In fact, as seen in Figure 3.3, the relative risk aversion coefficient peaks when the initial state belong to 25-50 percentage range (for $\rho_{rc} > 0$), or when the initial state belong to 50-75 percentage range (for $\rho_{rc} = 0$). In the first case, $\rho_{rc} > 0$, the maximum relative risk aversion coefficient goes to 15.7 as $\rho_{rc} \to 0$. However, when $\rho_{rc} = 0$, the maximum risk aversion coefficient is 16.5. Again, most of the results are in the 2-10 interval, except for the case when the initial case belongs to the 25-50 percentage inflation range.

The results show that there is an interval of realized inflation rates for which the relative risk aversion coefficient shows a positive relation with inflation. For the pooled sample, this range is for inflation between 5 and 50 percent (5 and 75 percent if $\rho_{rc} = 0$), as seen in Figure 3.2. For inflation levels above 50 percent (75 percent if $\rho_{rc} = 0$)

the relative risk aversion coefficient decreases. That is, once a really high inflation regime is reached, the positive relation between the price of risk and inflation does not hold any more.

The second approach relies on the assumption of a linear relation between the relative risk aversion coefficients of different regimes. In particular, I calculate the relative risk aversion coefficient of Regime K=3,...8, given different coefficients for Regime 2. The results are presented in Table 3.9, again when working with all the countries in the sample. In the first column the table the relative risk aversion coefficients for Regime 2 (inflation range 0-3%) are presented, starting in 2 and ending in 20. Columns 2-7 present the estimated values for the risk aversion coefficients for higher inflation regimes. Again, the results show that when inflation range increases, the implicit risk aversion coefficient only increase for the inflation range going from 10 to 50 percent. For inflation levels both below and above that range, the price of risk does not present a positive relation with the price variation.

Figure 3.3 plots some of the cases presented in Table 3.9, for a better understanding of the output. I present the results when the relative risk aversion in Regime 2 equals 2, 4, 6, 8, 10 and 12. When Regime 2 risk aversion coefficient is below 8, there is almost no implicit risk aversion coefficients above that threshold for higher inflation regimes. That is, there are almost no inflation ranges for which inflation and the price of risk show a positive relation. The results change if Regime-2 risk aversion coefficient is equal or higher than 8. In this case, for inflation regimes in the range 10-50 percentage, there is a clear positive relation between the implicit price of risk and inflation. It is worth to emphasize that in when working with Regime-dependent Euler conditions to get the implicit risk aversion coefficients, for Regime 2 this value is always above 8, independently of the consumption and real return innovations correlation.

These results thus confirm the previous findings. For the complete country sample, inflation correlates positively with the price of risk for a range between 10 and 50 percent. When inflation level belongs to 0-10 percentage range, I do not find evidence for a positive relation between inflation and the price of risk, while the same happens if inflation rate is above 50 percent. It is worth to note that, as seen in previous section, uncertainty does correlate positively with inflation for all inflation ranges. However, the results do not present evidence for the assumption of a monotonic relation between inflation and the risk aversion. This relation only holds for inflation rates in the 10-50 percentage range.

3.4.2.2 Epstein-Zin-Weil Preferences

One mayor caveat of power utility is that the coefficient of risk aversion is constrained to equal the reciprocal of the inter-temporal elasticity of substitution (IES). As discussed in Bansal and Yaron (2004), this brings up a number of conterfactual predictions. Maybe the most important one is that an increase in uncertainty would imply a lower dividend yield (stock price increases). Barro (2009) departs from power utility, mainly from the restriction of risk aversion coefficient being equal to the reciprocal of the IES, using Epstein-Zin-Weil preferences to test whether the macro-disaster probability still explains the equity premium. In this section, I use the correction in Barro (2009) to test if the constraint in the power utility model is driving the results.

Barro (2009) shows that under i.i.d. shocks, the conditions for the asset pricing under EZW preferences are similar to those in the power-utility model. In fact, only by correcting the rate of time preference in Euler condition go can translate the condition to EZW preferences. The correction in Barro (2009) takes the following form:

$$\delta^* = \delta - (\gamma - \vartheta)\left\{\triangle c_{t+1} - 0.5\,\gamma\sigma_c^2\right\}$$

where δ^* is the corrected rate of time preference, and ϑ is the reciprocal of the IES. As before, γ is the coefficient of relative risk aversion.

I repeat the first strategy, finding the coefficient of relative risk aversion that is solution for Equation 3 in each Regime, but in this case including the correction so to avoid the restriction on both the coefficient of relative risk aversion and the IES. In Table 3.8, I present the results for all positive inflation rate regimes, using $\vartheta = 0.5$. The results confirm the previous relations. First, in most cases the coefficients of relative risk aversion are lower than when working with power utility. In fact, most of the coefficients are close to 4, which is the benchmark value in calibrations (see Barro, 2005). Second, for inflation ranges (3 to 5 percent) and (5 to 10 percent), the risk aversion coefficient decreases when compared to the implicit coefficient for inflation range 0 to 3 percent. Third, for inflation levels above 10 percent, implicit relative risk aversion increases to peak in the 25 to 50 percent range. The exception in these cases are for small values of correlation for the consumption growth and real return innovations. The extreme is for the correlation being equal to zero, in which case the relative risk aversion coefficient keeps increasing with inflation. For correlation values above 0.3, the implicit relative risk aversion coefficient decreases when conditioning on Regimes 7 and 8 (inflation rates above 50 percent).

The second approach is repeated under EZW preferences. The second approach relies on the assumption of a linear relation between the relative risk aversion coefficients of different regimes. As before, given the coefficient for Regime 2, I find the implicit relative risk aversion coefficient for Regime 3 to 8. When relaxing the constraint between relative risk aversion and IES, the implicit coefficients are higher than when the constraint is binding. Four cases are plotted in Figure 3.4. In each case, I compare the RRA coefficients for different levels in Regime 2. In the first case, RRA coefficient in Regime 2 is 4. Note that, when compared to the power utility case, the implicit coefficients for different inflation regimes are now higher. This is particularly important, in the previous case for RRA coefficients lower than 8 for Regime 2 the results were not informative. In the figure, this is seen in the negative slope of the Regime-implicit RRA coefficients. Moreover, for very high inflation ranges, the implicit RRA coefficient is negative. When the constraint on both the RRA and IES is relaxed, the results show lower RRA coefficient for regimes 3 and 4, but significantly higher for Regimes 5 and 6. There is no qualitative differences when Regime 2 RRA coefficient is assumed to be higher (6, 8, and 10). In all cases, the implicit RRA is higher than when working with power utility.

The main conclusions can be summarized as follows. First, there is evidence that the price of risk increases with inflation. However, the evidence shows that this is true only when inflation is in the 10-50 percentage range. Second, implicit relative risk aversion marginally decreases with inflation in the 0-5 percentage range, while the relation seems to be insignificant in the 5-10 range. Third, the results show that for inflation rates above 50 percent, relative risk aversion decreases with inflation. Four, the implicit RRA coefficients are better behaved (i.e. the coefficients are between 2 and 10 as discussed in Gollier (2002) if the constraint on both RRA and IES imposed in the power utility is relaxed.

3.5 Stagflation Risk

3.5.1 Stagflations as Macro-Disasters

Stagflations are periods of both low or negative income growth and high inflation. These phenomena have been very common in the seventies, when oil prices spikes put severe stress on both relative prices and good prices. The outcome was a period of prolonged and strong inflationary process. In this paper, a stagflation is considered a disaster macro event. For stock market returns stagflation periods prove to be as damaging as wars or devaluations. Stagflations periods are common to both developed and emerging countries. In developed countries average inflation rates have been lower than in emerging countries. However, the impact of inflation on real cumulative returns has been severe in both developed and emerging countries.

In Table 3.10 a sample of stagflation events are presented. I present cases for both inflationary and hyperinflationary cases, for both Developed and Emerging countries. The first part of the table introduces the cases of Australia, Austria, Canada, France, Germany, Spain; and the US for Developed markets; and Brazil and Colombia for Emerging countries. The second part of Table 3.10 includes some examples of hyperinflations. I analyze Germany in the 20s, Brazil in the 90s and Israel in the 70s.

Stagflations present three basic dimensions: i) the episodes are long-lived; ii) average inflation rate over the period are high; and iii) cumulative real stock return is strongly negative. For the cases reviewed in Table 3.10, the average duration of the stagflation period is 28.2 quarters, while the median duration is 21.0 quarters. Note that duration of hyperinflation cases is significantly lower than stagflation periods. Second, the average inflation rate is higher than for other periods. For these selected cases, average inflation rate is 22.2 percent, while the median is 12.3 percent on an annual basis. Finally, cumulative real returns are negative. In other words, the real value index for the stock market decreases monotonically during the stagflation period. The interval of real stock price decrease goes from -34.9 percent (Germany 70s) to -91.8 percent (Spain 70s). Note the brutal impact on annual real returns: -12.9 percent for the average case, and -15.9 for the median case. Interesting point is that nominal returns may increase during the stagflation period (in the table this is the case of Colombia and all the hyperinflation countries). In these cases, real returns are negative because of the inflation cumulative effects.

To understand the inflation effect on real returns, in the last two columns of Table 3.10, I disentangle the effect of nominal cumulative returns and cumulative inflation when explaining the cumulative real returns. For example, in the case of Australia, 67.8 percent of the cumulative real return is explained by inflation and whether 32.2 percent is explained by negative cumulative nominal returns. In this case, both nominal cumulative returns and inflation erode the real cumulative return. However, this is not always the case. Take Colombia for example. Colombia experienced a prolonged stagflation period (61 quarters). During that period, nominal cumulative returns increased by 157.8 percent. However, the impact of inflation was even higher, as cumulative inflation explains more than a hundred percent of the fall in real cumulative returns (144.8 percent is explained by inflation). On average, inflation explains 92.4 percent of the cumulative decrease in real stock prices, while nominal decrease in stock prices explains only 7.6 percent. See Figure 3.5 for the cases of Israel, Spain and Colombia.

The fact that most of the cumulative decrease in real stock prices is explained by inflation is reinforced when analyzing the hyperinflation events. For these cases, inflation explains 756.3 percent of the fall in the real stock prices, while the increase in nominal stock prices explains 656.3 percent (note that, to control for the impact of the complete German hyperinflation, in this case the average of the case decompositions is used).

3.5.2 Regime-Conditional Probability of a Stock Price Collapse

A real stock price collapse is defined for the cases in which the real stock price decreases more than fifty percent in a cumulative way. That is, when in subsequent periods real stock price decreases from peak to through more than fifty percent. Note that, in the definition, a decrease of 20 percent in one quarter, followed by subsequent increases in real stock prices is not considered a collapse. I restrict the maximum duration of the episode to be ten years. As discussed in the previous section, the average stagflation episode last 7 years and 2 months, while the median episode duration is 5 years and one quarter.

From the previous section, we know that:

- a) higher inflation ranges are negatively related with real returns. The higher the inflation, the lower real stock returns;
- b) for higher inflation ranges, the longer the duration of very high inflation regimes (only for Emerging Countries and the complete sample).

These conditions, however, are not sufficient conditions to observe a real stock price collapse, as defined before. Moreover, I want to test if for higher inflation ranges, the probability of observing a collapse in real stock prices increases.

Table 3.11 reports the simulated probability of observing a collapse in real stock prices for Developed, European, Emerging and All countries in the sample. Starting with the Developed Country sample, for Regime 1, the conditional probability of suffering a collapse in real stock prices is 0.00250. The probability increases with the inflation ranges, peaking in Regime 6 (inflation range 10-25 percent), being the probability 0.00370. Thus, the probability of suffering a collapse increases with inflation ranges.

When working with European countries, the probability of suffering a collapse in real stock prices notably increases when compared to the Developed Country cases. When inflation rates are negative the probability is 0.0472. As before, the probability increases in a monotonic way, peaking in Regime 6 at a 0.0613 value. These results are somehow surprising, in particular because condition b) is not true for both Developed and European countries. The probability of a real collapse in stock prices is then increasing in inflation, even in Developed and European countries.

The Emerging market case increases the support for the positive relation between inflation and the probability of a collapse. There are two points worthy to discuss. First, the probability of a collapse makes a dramatic jump with respect to the Developed and European cases, being more than five times higher. Second, a puzzling result is that the probability of a collapse in real stock prices is higher in Regime 1 than in Regimes 2 and 3. In other words, the probability of a collapse is higher when inflation rates are negative than when inflation is in the 0-5 percentage range. This result is a priori expected for Developed Countries, in particular when having in mind the Great Depression. However, it is only true for Emerging Markets, at least when working with the 1960 - 2010 period.

The last column of Table 3.11 reports the results from pooling all the countries in the sample. Conditional on the initial state being in Regime 1, the probability of a collapse in stock prices is 0.034. For the 0 to 3 percent inflation range, the probability decreases to 0.032, slightly lower than in Regime 1. The probability increases for Regime 3 when compared to Regime 2, and keeps increasing for higher inflation ranges. The probability peaks then in Regime 8, at a 0.70 level. Therefore, for positive inflation rates, the simulations show a positive correlation between inflation and the probability of a real stock price collapse.

The results support the explanation in Chapter 2 of this dissertation. To explain the positive relation between inflation and dividend yields, I suggest that agents may use realized inflation rate as a proxy for the probability of a stagflation episode. It is worth to emphasize that this risk factor does not have a perfect correlation with risk aversion, in particular in the case of Developed Countries. I find that the price of risk does not increase with inflation for Developed countries. However, the risk of stagflation is proved to have a positive relation with the realized inflation rate (or expected inflation rates).

3.6 Conclusions

In this paper, I test whether macroeconomic data provide evidence for both the relation between inflation and uncertainty, and the relation between inflation and the price of risk (i.e. relative risk aversion). The results show that both relations do not have robust support when inflation rates are below 10 percent (annualized rates). For inflation rates above that threshold, there is indeed a positive relation between inflation and uncertainty, and inflation and the price of risk.

On the inflation and uncertainty relationship, the results show that there is a strong relation between inflation and uncertainty, but only for inflation levels above 10 percent (on an annual basis). For inflation below that threshold, there is not clear evidence on a positive relation. Average consumption growth rates do not show a declining trend when inflation rates are in the 0-10 percentage range. The same is true for the volatility of real consumption growth rates. However, for inflation levels above 10 percent, consumption growth rates decline while volatility increases. Working with real stock returns tells a similar story. The main difference is that, when inflation is in the 0-10 percentage range, realized average real stock returns decrease as inflation increases. However, there is not a robust trend for volatility in that inflation range. For inflation ranges above 10 percent, real returns decrease as volatility increases.

On the inflation and risk price (relative risk aversion) relationship, the results again present a robust correlation, but only for intermediate inflation ranges. When pooling all countries in the sample, the positive relation between inflation and relative risk aversion is present for inflation ranges between 10 and 50 percent. For lower inflation regimes, the positive relation is not robust. Moreover, for inflation rates above 50 percent, risk aversion decreases. The results are robust to power utility and Epstein-Zin-Weil preferences. These results raise doubts on the assumptions of relative risk aversion as a function of inflation innovations as in Brandt and Wang (2003).

Finally, I test with the same dataset the explanation suggested in Chapter 2 for the positive correlation between inflation and risk aversion (and uncertainty). Working with simulations, I find the probability of suffering a real stock price collapse, defined as a fall higher than fifty percent in a ten year period from peak to trough. The results show that the probability increases for higher inflation ranges in a monotonic way, for the different subsamples (Developed, European, Emerging and Pooled samples). Therefore, while both the inflation-uncertainty and the inflation-risk aversion relationships are not robust for inflation rates in the 0 to 10 percent inflation range, the probability of suffering a real stock price collapse does increase in all inflation ranges.

Table 3.1: Country Sample

Developed	European	Emerging
Australia	Austria	Argentina
Canada	Belgium	Bahrain
France	Bulgaria	Bangladesh
Germany	Denmark	Botswana
Japan	Greece	Brazil
Switzerland	Hungary	Colombia
UK	Ireland	Indonesia
USA	Italy	Israel
	Portugal	Kenya
	Spain	Korea
	Sweden	Kuwait
		Lebanon
		Malaysia
		Mexico
		Morocco
		Quatar
		Saudi Arabia
		Singapore
		Sri Lanka
		Syria
		Thailand
		Trinidad and Tobago
		Venezuela
		Vietnam

Table 3.2: Inflation Regimes

Notes: The table reports the inflation rate ranges used in the paper in order to define the different Regimes. π stands for inflation rates. For every quarter, a country is allocated to each regime only by the (annualized) inflation rate. Regime 1 is for negative inflation rates. Regime 2 is for inflation rate in the 0-3 percent range, Regime 3 is for inflation rate in the 3-5 percent range, Regime 4 is for inflation rate in the 5-10 percent range, Regime 5 is for inflation rate in the 10-25 percent range, Regime 6 is for inflation rate in the 25-50 percent range, Regime 7 is for inflation rate in the 50-75 percent range, and Regime 8 is for inflation rates above 75 percent. Quarterly data, 1960-2011.

Regime	Inflation Rate Range
1	$\pi < 0$
2	$0 < \pi < 0.03$
3	$0.03 < \pi < 0.05$
4	$0.05 < \pi < 0.10$
5	$0.10 < \pi < 0.25$
6	$0.25 < \pi < 0.50$
7	$0.50 < \pi < 0.75$
8	$\pi > 0.75$

Table 3.3: Regime Transition Matrices

Notes: The table reports the frequencies with which the inflation rate in the following year is in different ranges. The present state is defined per row, while future ranges are in columns. For instance, in the case of Developed Countries subsample, if the inflation rate in year t is negative, then the probability that inflation will be in the 0 to 3 percent inflation range in year t+1 is 0.4112 (corresponds to first row, second column entry). Each regime is defined in relation to the inflation rate. Regime 1 is for negative inflation rates. Regime 2 is for inflation rate in the 0-3 % range, Regime 3 is for inflation rate in the 3-5 percent range, Regime 4 is for inflation rate in the 5-10 percent range, Regime 5 is for inflation rate in the 10-25 percent range, Regime 6 is for inflation rate in the 25-50 percent range, Regime 7 is for inflation rate in the 50-75 percent range, and Regime 8 is for inflation rates above 75 percent.

DEVELOPED COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6
Reg 1	0.1145	0.4112	0.2247	0.194	0.0535	0.002
Reg 2	0.1137	0.4089	0.2243	0.1955	0.0555	0.0022
Reg 3	0.1082	0.3934	0.2229	0.2058	0.0666	0.0031
Reg 4	0.0954	0.3556	0.2171	0.2296	0.0964	0.0058
Reg 5	0.0692	0.275	0.1992	0.2776	0.166	0.013
Reg 6	0.0605	0.2478	0.1922	0.2934	0.1905	0.0157

EUROPEAN COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6
Reg 1	0.0859	0.3437	0.2257	0.2388	0.1022	0.0036
Reg 2	0.086	0.3446	0.2262	0.2386	0.101	0.0036
Reg 3	0.0831	0.3231	0.2193	0.2515	0.1187	0.0044
Reg 4	0.0785	0.2894	0.2083	0.2714	0.1467	0.0057
Reg 5	0.0696	0.2325	0.1873	0.3001	0.2022	0.0083
Reg 6	0.0662	0.2103	0.1792	0.3117	0.2234	0.0093

Table 3.3. Continuation

Notes: The table reports the frequencies with which the inflation rate in the following year is in different ranges. The present state is defined per row, while future ranges are in columns. For instance, in the case of Developed Countries subsample, if the inflation rate in year t is negative, then the probability that inflation will be in the 0 to 3 percent inflation range in year t+1 is 0.4112 (corresponds to first row, second column entry). Each regime is defined in relation to the inflation rate. Regime 1 is for negative inflation rates. Regime 2 is for inflation rate in the 0-3 % range, Regime 3 is for inflation rate in the 3-5 percent range, Regime 4 is for inflation rate in the 5-10 percent range, Regime 5 is for inflation rate in the 10-25 percent range, Regime 6 is for inflation rate in the 25-50 percent range, Regime 7 is for inflation rate in the 50-75 percent range, and Regime 8 is for inflation rates above 75 percent.

EMERGING COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
Reg 1	0.1218	0.2092	0.1299	0.2278	0.2229	0.065	0.0102	0.0132
Reg 2	0.1242	0.2154	0.1331	0.2306	0.2192	0.0602	0.0086	0.0088
Reg 3	0.1179	0.2008	0.1272	0.2279	0.2315	0.0706	0.0112	0.0129
Reg 4	0.1134	0.1898	0.1226	0.2257	0.2414	0.0789	0.0131	0.0153
Reg 5	0.1	0.1595	0.1074	0.2118	0.2601	0.1047	0.0217	0.0348
Reg 6	0.0814	0.1206	0.0856	0.1836	0.2661	0.1369	0.0383	0.0875
Reg 7	0.051	0.0653	0.0492	0.1156	0.2121	0.163	0.0755	0.2682
Reg 8	0.027	0.0264	0.0216	0.0545	0.1337	0.1572	0.106	0.4737

ALL COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
Reg 1	0.1068	0.2657	0.1671	0.2294	0.1684	0.0432	0.0071	0.0122
Reg 2	0.1097	0.2831	0.1749	0.2296	0.157	0.0353	0.0048	0.0057
Reg 3	0.1038	0.2574	0.1689	0.2357	0.1754	0.0444	0.0066	0.0079
Reg 4	0.0981	0.2287	0.1574	0.2407	0.1985	0.057	0.0089	0.0107
Reg 5	0.0863	0.1824	0.1323	0.2309	0.2334	0.0887	0.0176	0.0283
Reg 6	0.0705	0.1293	0.0994	0.201	0.253	0.131	0.0351	0.0806
Reg 7	0.0459	0.0668	0.0541	0.1256	0.208	0.1654	0.073	0.261
Reg 8	0.0277	0.0298	0.0256	0.0616	0.1342	0.1607	0.1029	0.4577

Table 3.4: Regime-Conditional Consumption Growth Rates

The table reports summary statistics for the Regime-conditional consumption growth rates distribution. Each regime is defined in relation to the inflation rate. Regime 1 is for negative inflation rates. Regime 2 is for inflation rate in the 0-3 percent range, Regime 3 is for inflation rate in the 3-5 percent range, Regime 4 is for inflation rate in the 5-10 percent range, Regime 5 is for inflation rate in the 10-25 percent range, Regime 6 is for inflation rate in the 25-50 percent range, Regime 7 is for inflation rate in the 50-75 percent range, and Regime 8 is for inflation rates above 75 percent.

		Developed Countries		European Countries		Emerging Countries		All Countries	
Reg	Inflation Range	Mean	Volatility	Mean	Volatility	Mean	Volatility	Mean	Volatility
1	$\pi < 0$	0.01929	0.00130	0.02131	0.00119	0.03062	0.00205	0.0295	0.00181
2	$0 < \pi < 0.03$	0.02634	0.00247	0.03023	0.00175	0.02635	0.00211	0.027	0.00179
3	$0.03 < \pi < 0.05$	0.02644	0.00376	0.02847	0.00236	0.02718	0.00436	0.02736	0.00378
4	$0.05 < \pi < 0.10$	0.0305	0.00312	0.02736	0.00192	0.02588	0.00305	0.02608	0.00265
5	$0.10 < \pi < 0.25$	0.02577	0.00303	0.02658	0.00201	0.01741	0.0043	0.01857	0.00376
6	$0.25 < \pi < 0.50$	0.02348	0.00664	0.02668	0.00465	-0.0352	0.00868	-0.03026	0.00808
7	$0.50 < \pi < 0.75$					-0.06749	0.02465	-0.06749	0.02465
8	$\pi > 0.75$					-0.09204	0.03236	-0.092	0.03236
Mean		0.02354	0.00096	0.02524	0.00074	0.02468	0.0013	0.02476	0.00113

Table 3.5: Regime-Conditional Real Return Moments (Annual Basis)

The table reports summary statistics for the Regime conditional real return distribution. R stands for Regime. Each regime is defined in relation to the inflation rate. Regime 1 is for negative inflation rates. Regime 2 is for inflation rate in the 0-3 percent range, Regime 3 is for inflation rate in the 3-5 percent range, Regime 4 is for inflation rate in the 5-10 percent range, Regime 5 is for inflation rate in the 10-25 percent range, Regime 6 is for inflation rate in the 25-50 percent range, Regime 7 is for inflation rate in the 50-75 percent range, and Regime 8 is for inflation rates above 75 percent. Volatility is the standard deviation of real returns. VaR(x%) stands for the threshold value such that the probability that the real return exceeds this value is x.

DEVELOPED COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
Inflation	**< 0%**	**0-3%**	**3-5%**	**5-10%**	**10-25%**	**25-50%**	**50-75%**	**> 75%**
Average	-0.024	0.0832	0.0351	0.0097	-0.081	-0.171	.	.
Volatility	0.1991	0.1564	0.1429	0.1262	0.1862	0.1894	.	.
VaR(1%)	-0.724	-0.663	-0.533	-0.424	-0.624	-0.403	.	.
VaR(99%)	0.9974	1.0577	0.9126	0.8294	1.4828	0.3999	.	.

EUROPEAN COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
Average	0.032	0.1217	0.0442	0.0313	-0.052	-0.392	.	.
Volatility	0.2502	0.1811	0.1683	0.1926	0.1917	0.1673	.	.
VaR(1%)	-0.820	-0.591	-0.586	-0.618	-0.578	-0.672	.	.
VaR(99%)	1.6399	1.6831	1.1806	2.0844	1.9655	0.084	.	.

EMERGING COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
Average	0.1621	0.1607	0.103	0.0537	0.0334	-0.037	-0.018	-0.063
Volatility	0.3134	0.263	0.2472	0.2503	0.2993	0.3489	0.4129	0.5384
VaR(1%)	-0.809	-0.764	-0.785	-0.791	-0.729	-0.822	-0.862	-0.978
VaR(99%)	4.7567	2.9435	2.5546	2.3319	5.9309	6.0756	4.5323	8.0753

ALL COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
Average	0.0858	0.1249	0.0657	0.0399	0.0061	-0.048	-0.018	-0.063
Volatility	0.2785	0.2101	0.1998	0.2182	0.2737	0.3458	0.4129	0.5384
VaR(1%)	-0.799	-0.681	-0.616	-0.697	-0.714	-0.819	-0.862	-0.978
VaR(99%)	3.1216	2.2135	2.1288	2.1614	4.5627	6.0544	4.5323	8.0753

Table 3.6: Simulated Annual Returns

The table reports the simulations for regime-conditional real stock returns, working with Normal distributions and the actual (empirical) regime conditional distributions. Simulations are performed for Developed, European, and Emerging countries, and for all the countries in the sample (pooled sample). I use regime conditional transition probability matrices, and use the empirical conditional distributions of real returns. The procedure is repeated a 1,000,000 times. The Esscher transformation is used to simulate Markov switching regimes.

DEVELOPED COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
Normal Dist	-0.001	0.0445	0.0147	0.0123	-0.070	-0.046	.	.
Actual Dist	0.0357	0.0351	0.0329	0.0271	0.0137	0.0090	.	.
STD (Actual Dist)	0.1004	0.0100	0.1000	0.0992	0.0982	0.0976		

EUROPEAN COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
Normal Dist	0.1172	0.1177	0.0995	0.0714	0.0214	0.0028	.	.
Actual Dist	0.0964	0.0951	0.079	0.0539	0.0092	-0.006	.	.
STD (Actual Dist)	0.3892	0.1722	0.1714	0.1712	0.2198	0.3800		

EMERGING COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
Normal Dist	0.2664	0.2798	0.2543	0.2369	0.1788	0.0901	-0.075	-0.208
Actual Dist	0.2157	0.2252	0.2035	0.191	0.1407	0.0668	-0.073	-0.179
STD (Actual Dist)	0.3588	0.3570	0.3590	0.3584	0.3624	0.3678	0.3762	0.3842

ALL COUNTRIES

	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
Normal Dist	0.1555	0.1655	0.1485	0.1266	0.0737	-0.001	-0.135	-0.239
Actual Dist	0.1192	0.1361	0.1103	0.0935	0.049	-0.018	-0.127	-0.207
STD (Actual Dist)	0.5100	0.4942	0.4984	0.5101	0.5402	0.596	0.7439	0.8562

Table 3.7: Regime-Implicit Relative Risk Aversion

The table reports regime-conditional implicit relative risk aversion (RRA) coefficient, when working with all countries in the sample. The different columns correspond to different consumption and real return innovations covariances, σ_{rc}. I work with different values for the correlation of consumption and real return innovations, given that $\sigma_{rc}\rho_{rc} = \sigma_r\sigma_c$. The implicit RRA coefficient is found solving the Euler condition under Power Utility Function. The pooled sample regime-conditional moments for consumption growth rates and regime-conditional actual real return distributions are used in the calibrations. Expected real returns are simulated using regime transition probability matrices.

	Correlation				
	0.0	**0.4**	**0.6**	**1.0**	**Regime Dependant**
$0 < \pi < 0.03$	8.9	8.8	8.7	8.6	8.8 ($\rho = 0.3$)
$0.03 < \pi < 0.05$	8.1	7.9	7.8	7.6	7.9 ($\rho = 0.4$)
$0.05 < \pi < 0.10$	8.1	7.9	7.8	7.7	7.9 ($\rho = 0.5$)
$0.10 < \pi < 0.25$	9.7	9.3	9.1	8.8	9.1 ($\rho = 0.6$)
$0.25 < \pi < 0.50$	15.7	12.9	11.9	10.3	11.4 ($\rho = 0.7$)
$0.50 < \pi < 0.75$	16.5	8.9	6.9	4.9	5.7 ($\rho = 0.8$)
$\pi > 0.75$	9.5	7.1	5.2	3.4	3.8 ($\rho = 0.9$)

Table 3.8: Regime-Implicit Relative Risk Aversion. Epstein-Zin-Weil Preferences

The table reports regime-conditional implicit relative risk aversion coefficient, when working with all countries in the sample. The different columns correspond to different consumption and real return innovations covariances, σ_{rc}. I work with different values for the correlation of consumption and real return innovations, given that $\sigma_{rc}\rho_{rc} = \sigma_r \sigma_c$. The implicit RRA coefficient is found solving the Euler condition under Epstein-Zin-Weil preferences. The pooled sample regime-conditional moments for consumption growth rates and regime-conditional actual real return distributions are used in the calibrations. Expected real returns are simulated using regime transition probability matrices.

	Correlation				
	0.0	**0.4**	**0.6**	**1.0**	**Regime Dependant**
$0 < \pi < 0.03$	4.5	4.5	4.5	4.5	4.5 ($\rho = 0.3$)
$0.03 < \pi < 0.05$	4.2	4.1	4.1	4.1	4.2 ($\rho = 0.4$)
$0.05 < \pi < 0.10$	4.2	4.1	4.1	4.1	4.2 ($\rho = 0.5$)
$0.10 < \pi < 0.25$	5.0	4.9	4.8	4.7	4.9 ($\rho = 0.6$)
$0.25 < \pi < 0.50$	7.7	7.0	6.7	6.2	7.3 ($\rho = 0.7$)
$0.50 < \pi < 0.75$	9.0	5.6	4.8	3.7	6.8 ($\rho = 0.8$)
$\pi > 0.75$	10.1	4.9	3.9	2.9	6.8 ($\rho = 0.9$)

Table 3.9: Implicit Relative Risk Aversion Relative to Reg-2

The table reports the implicit relative risk aversion coefficient from solving Equation (2) for given values of risk aversion in Regime-2, for any K=3, 4, 5, 6, 7 and 8. I use the assumption of a linear relation between the conditional risk aversion coefficients, that is, $\frac{\gamma_{s=L}}{\gamma_{s=2}} = Constant$. The implicit RRA coefficient is found solving the Euler condition under Power Utility Function. The pooled sample regime-conditional moments for consumption growth rates and regime-conditional actual real return distributions are used in the calibrations. Expected real returns are simulated using regime transition probability matrices.

Regime 2 0-3%	Regime 3 3-5%	Regime 4 5-10%	Regime 5 10-25%	Regime 6 25-50%	Regime 7 50-75%	Regime 8 >75%
2	1.2	0.9	0.0	-2.4	-1.9	-1.6
3	2.2	2.0	1.3	-0.5	-0.9	-0.8
4	3.1	3.0	2.6	1.4	0.1	-0.1
5	4.1	4.0	4.0	3.3	1.1	0.6
6	5.1	5.0	5.3	5.2	2.1	1.4
7	6.0	6.0	6.6	7.1	3.1	2.2
8	7.0	7.1	8.0	9.1	4.2	3.0
9	8.0	8.1	9.3	11.1	5.3	3.8
10	8.9	9.1	10.6	13.0	6.4	4.6
11	9.9	10.1	12.0	15.0	7.6	5.5
12	10.9	11.1	13.3	17.1	8.8	6.4
13	11.9	12.2	14.6	19.1	10.0	7.3
14	12.8	13.2	16.0	21.2	11.3	8.2
15	13.8	14.2	17.3	23.3	12.6	9.2
16	14.8	15.2	18.6	25.4	14.0	10.2
17	15.7	16.2	20.0	27.5	15.4	11.2
18	16.7	17.3	21.3	29.6	16.9	12.3
19	17.7	18.3	22.7	31.8	18.5	13.5
20	18.6	19.3	24.0	34.0	20.2	14.7

Table 3.10: Stagflations and Hyperinflations, Selected Cases

Stagflation Episodes							
					% Explained by:		
	Initial Date	Cum. Inflation	Cum. Nominal Returns	Cum. Real Returns	Inflation	Nominal Decrease	Quarters
Australia	73Q1	0.837	-0.251	-0.592	67.80%	32.20%	20
Austria	73Q2	0.917	-0.272	-0.62	67.20%	32.80%	46
Canada	73Q1	0.51	-0.203	-0.472	64.50%	35.50%	21
Colombia	71Q1	20.385	1.578	-0.879	144.80%	-44.80%	61
France	73Q2	0.531	-0.441	-0.635	42.30%	57.70%	17
Spain	74Q1	3.148	-0.66	-0.918	56.90%	43.10%	37
Germany	72QII	0.183	-0.23	-0.349	39.10%	60.90%	6
US	73QI	0.218	-0.434	-0.535	25.80%	74.20%	8
Average		**3.113**	**-0.11**	**-0.622**	**92.40%**	**7.60%**	**28.2**
Median		**0.837**	**-0.251**	**-0.596**	**67.80%**	**32.20%**	**21**
Memo:							
US	73QI	1.289	-0.076	-0.596	91.30%	8.70%	38

Table 3.10: Stagflations and Hyperinflations, Selected Cases (Cont.)

Hyperinflation Episodes							
					% Explained by:		
	Initial Date	Cum. Inflation	Cum. Nominal Returns	Cum. Real Returns	Inflation	Nominal Decrease	Quarters
Brazil	94Q1	4.04	2.06	-0.393	324.40%	-224.40%	4
Israel	73Q1	1312.5	192.9	-0.852	375.30%	-275.30%	31
Germany 20s	21QIV	11.4	1.27	-0.817	148.30%	-48.30%	5
Average		**442.7**	**65.4**	**-0.687**	**282.60%**	**-182.60%**	**13.3**
Median		**11.4**	**2.1**	**-0.817**	**324.40%**	**-224.40%**	**5**
Memo:							
Israel II	73Q1	7059.8	618.0	-0.912	364.10%	-264.10%	52
Germany 20s	21QIV	80265339966	30207981469	-0.624	2569.40%	-2469.40%	8

Table 3.11: Regime-Conditional Probability of Real Stock Price Collapse

The table reports the regime conditional probability of experiencing a real stock price collapse. A collapse is defined as a fall higher than fifty percent in a ten year period from peak to trough. The period for the simulations reported is ten years. Regime 1 is for negative inflation rates. Regime 2 is for inflation rate in the 0-3 percent range, Regime 3 is for inflation rate in the 3-5 percent range, Regime 4 is for inflation rate in the 5-10 percent range, Regime 5 is for inflation rate in the 10-25 percent range, Regime 6 is for inflation rate in the 25-50 percent range, Regime 7 is for inflation rate in the 50-75 percent range, and Regime 8 is for inflation rates above 75 percent.

	Developed	**European**	**Emerging**	**All**
Regime 1	0.00250	0.0472	0.24142	0.0336
Regime 2	0.00289	0.0473	0.22206	0.0316
Regime 3	0.00293	0.0475	0.23982	0.0301
Regime 4	0.00323	0.0516	0.26095	0.0408
Regime 5	0.00358	0.0591	0.31322	0.1160
Regime 6	0.00370	0.0613	0.46207	0.1715
Regime 7			0.74904	0.4679
Regime 8			0.89907	0.7006

Figure 3.1: Regime-Conditional Distributions for Quarterly Real Returns (All Countries)

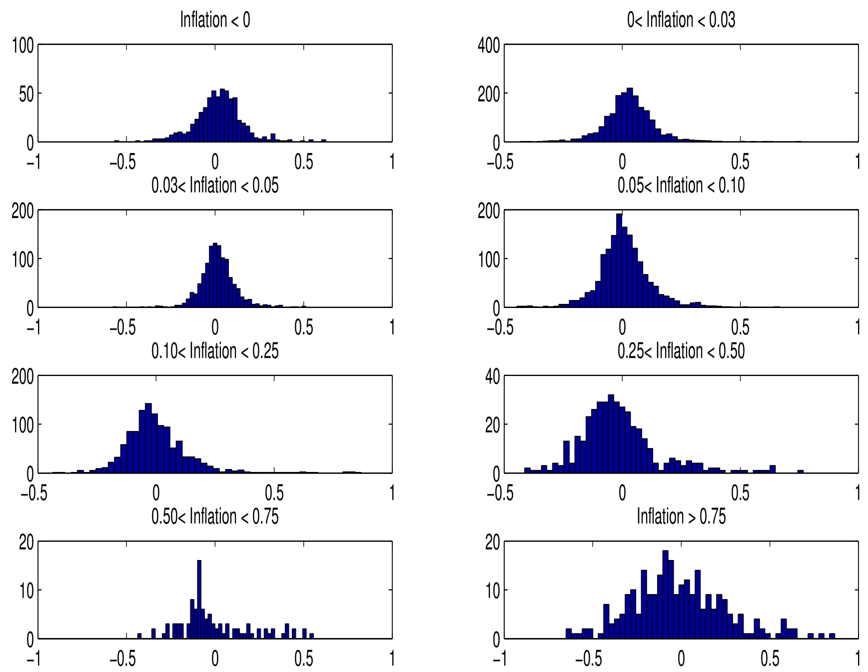


Figure 3.2: Regime-Implicit Relative Risk Aversion (All Countries)

The figure shows the regime-conditional implicit relative risk aversion coefficient, when working with all countries in the sample. The different curves correspond to different consumption and real return innovations covariances, σ_{rc}. I work with different values for the correlation of consumption and real return innovations, given that $\sigma_{rc}\rho_{rc} = \sigma_r\sigma_c$.

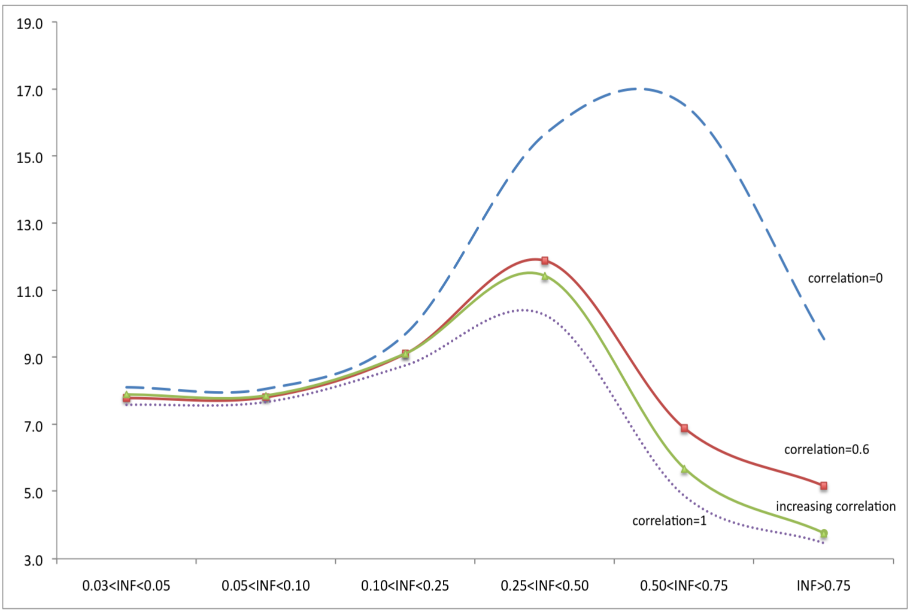


Figure 3.3: Implicit Relative Risk Aversion Relative to Regime 2 (All Countries)

The figure shows the implicit relative risk aversion coefficient from solving Equation (2) for given values of risk aversion in Regime-2, for any K=3, 4, 5, 6, 7 and 8. I use the assumption of a linear relation between the conditional risk aversion coefficients, that is, $\frac{\gamma_{s=L}}{\gamma_{s=2}} = Constant$.

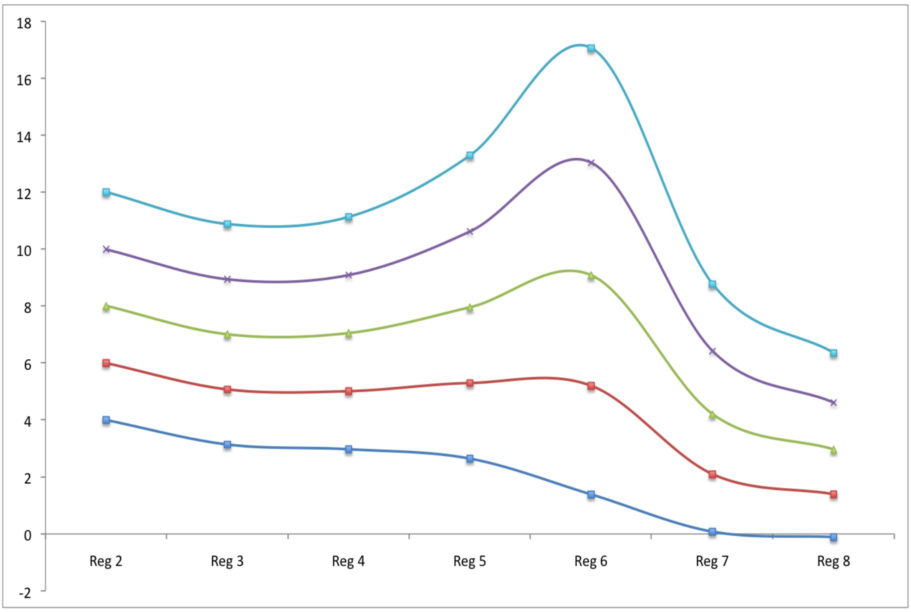


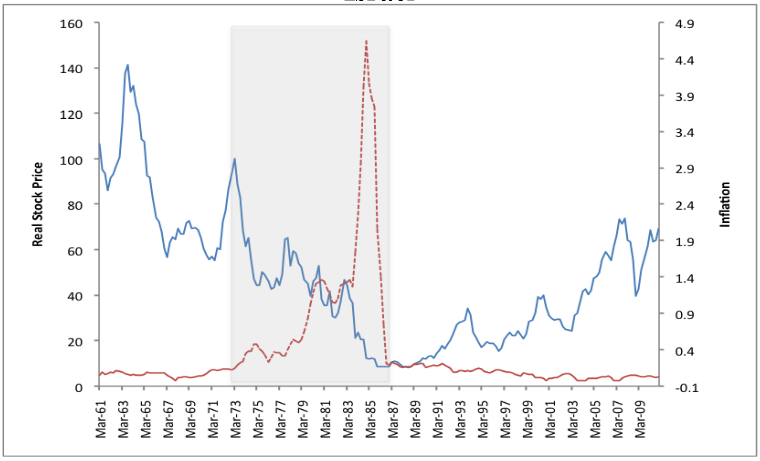
Figure 3.4: Implicit Relative Risk Aversion Relative to Regime 2

The figure shows the implicit relative risk aversion coefficient from solving Equation (2) for given values of risk aversion in Regime-2, for any K=3, 4, 5, 6, 7 and 8. I use the assumption of a linear relation between the conditional risk aversion coefficients, that is, $\frac{\gamma_{s=L}}{\gamma_{s=2}} = Constant$. The figure shows the difference in results when working under power utility preferences and Epstein-Zin-Weil preferences. The pooled sample regime-conditional moments for consumption growth rates and regime-conditional actual real return distributions are used in the calibrations. Expected real returns are simulated using regime transition probability matrices.

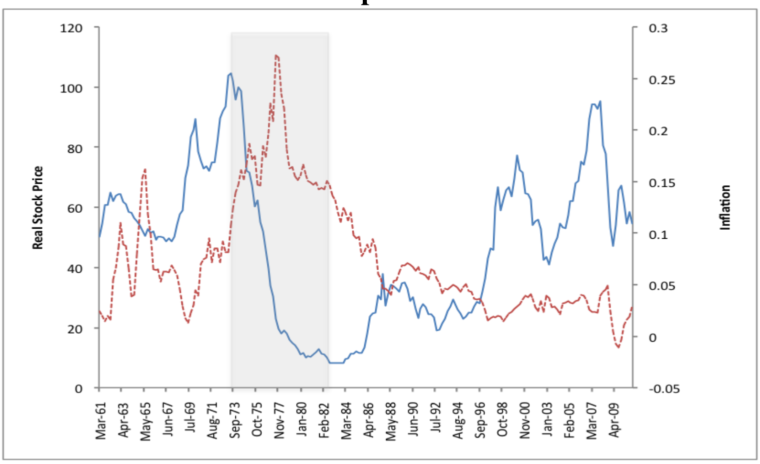
Figure 3.5: Inflation and Real Stock Prices

The figure shows three examples of stagflation. Real stock price (solid blue curve) is plotted on the left axis, 100= pre-stagflation peak. Inflation (dotted red curve) is plotted on the left axis.

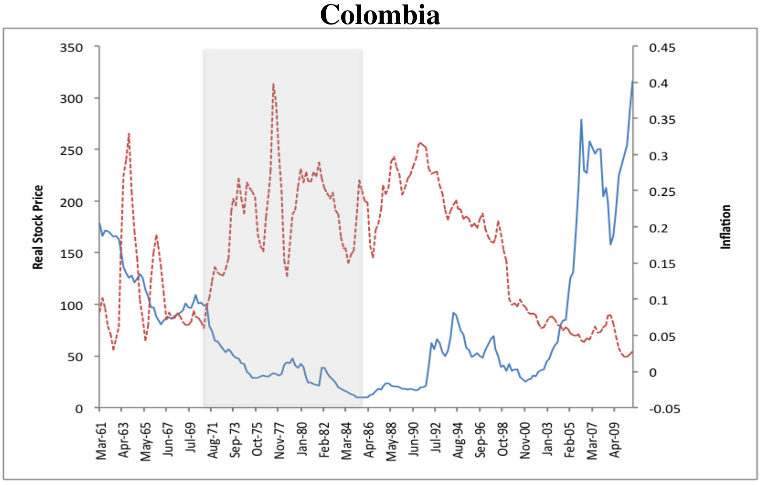
Israel



Spain



Colombia



4 Inflation and Risk Aversion: Rare-Event Premium or Money Illusion?

'Hyperinflations are the laboratory of monetary economics" (Rudiger Dornbusch)

4.1 Introduction

Is money illusion the driving force behind the negative correlation between inflation and real stock prices? Not necessarily. Pereira (2010) suggests that inflation enters in the stochastic discount factor as a proxy for the probability of a rare and catastrophic event. The rare-events in this setup are stagflation periods (hyperinflations in the limit). As inflation increases so does the probability of the bad state, driving rare-event risk premium higher and the stock price downward.

The main contribution of this paper is to use a historical case to show that it is the rare-event premium, not money illusion, what drives the negative relation between inflation and stock prices. While testing for money illusion is an elusive quest, I discuss two cases that help to differentiate the rare-event premium from money illusion. First, the rare-event premium is state-dependent while money illusion is not. Second, inflation must belong to the investment set (understood as the set of all dimensions relevant to an investment decision) for the rare-event premium explanation to make sense. However, this is not true in the case of money illusion. Even if price changes are not giving any information on future inflation rates, agents will continue to use nominal discount rates instead of real discount rates.

First, the rare-event premium is state-dependent. When the economy is in normal times, agents demand a premium for a potential bad state of nature. However, when the economy is in the bad state, the premium vanishes. The behavioral approach (e.g. money illusion), is not state dependent. A number of studies discuss the presence of money illusion (or other related behaviour) in high inflation regimes. For example, Shafir et al. (1997) claim that “residues of money illusion are observed even in highly inflationary environments”. Moreover, Fisher (1928) provides several interesting examples of inflation illusion during very high inflation periods, to be more precise during the German Hyperinflation[1]. I test the strength of this argument by using the hyperinflation period in Germany as the bad state of the economy. I find that in normal times, inflation correlates positively with the stock premium. However, that relation disappears during the high and hyper inflation period. This piece of evidence goes in line with the rare-event premium explanation and against the money illusion hypothesis.

Second, the main assumption behind the rare-event approach is that agents update the probability of the bad state using realized inflation rates. On the other side, the behavioral explanations point to inflation level as the driver of agent mistake, as they discount the future in nominal terms. I can test which of the two approaches is more grounded by using the role of inflation on expectations. If the agent does not incorporate the inflation rate in her investment set, the rare-event premium explanation ceases to make sense. As discussed below, the Gold Standard period presents two defined sub-periods, one in which price changes were never built into inflation expectations, and the other an ’inflationary’ Gold Standard subperiod. These two subperiods are useful to test whether it is the rare-event premium or money illusion what drives the correlation between inflation and real stock prices. As before, I find evidence in favor of the rare-event

[1]Other papers differ with respect to the presence of money illusion during hyperinflations. Barro (1972) tests the presence of money illusion in five hyperinflation episodes. The results strongly verify the absence of money illusion in three cases (Austria, Germany and Poland), but can not overrule money illusion in the two Hungarian episodes.

premium and against the money illusion hypothesis.

Following Campbell and Vuolteenaho (2004) and Brunnermeier and Julliard (2006), I decompose the dividend yield in long-run dividend growth rates and stock premium. The stock premium is assumed to be composed of two factors. The first factor depends linearly on the relative volatility of stock market returns with respect to bond market returns. The second factor is associated to money illusion à la Modigliani and Cohn (1979). It is worth to emphasize that this factor is observationally equivalent to the rare-event premium, except for the exceptions listed before, which enables to test both approaches.

This paper deals with inflation crisis, not the Great Depression deflation-type of crisis. Inflation crises are more common and more disruptive than deflation crises. Barro and Ursua (2008) include in their sample different GDP collapses, some of them related to deflation periods, and other to high or hyperinflation periods. The sample includes 102 collapses, with an average GDP collapse of 17.1 percent (19.3 percent average decrease in consumption). These numbers improve for collapses not related to war episodes (13.1 percent decrease in GDP and 14.5 percent in consumption). In Table 4.1, I restrict the sample to inflation crises, for which the figures are even more dramatic. For inflation crises, GDP falls on average 25.7 percent and consumption 27.3 percent. Again, when controlling for war periods, GDP falls 17.7 percent and consumption 19.4 percent. Hence, inflation crises are stronger than the average catastrophic event in Barro (2006).

I revisit the case of Germany between 1870 and 1935. For the whole period, the negative correlation between real stock returns and inflation is present in the case of Germany as shown in Table 4.2. Germany is a notable case of both extreme volatility and stability. In fact, these are periods that I use to test the rare-event premium dominance over money illusion. First, after WWI, the inflationary accommodative policy that Germany had followed in order to afford the reparation expenditures proved to be unsustainable. From June 1922 up to November 1923 Germany experienced the hyperinflation period. It was only after imposing dramatic policy measures that the authorities finally regained credibility both in the domestic and foreign fronts.

Second, it proves particularly useful the analysis of the Gold Standard period, since it presented two clear phases: the deflationary one (1870-1895), and the inflationary one (1895-1910). These phases were determined by the world gold production since money supply was tightened to gold reserves. Barsky and DeLong (1991) show that price changes during the period were never built into inflation expectations.

That inflation and real stock prices (returns) correlation is not zero is empirically well documented. The literature presents two approaches in order to explain the puzzle: the friction approach and the behavioral approach. In the first approach realized inflation affects future cash flows in different ways: i) the omitted factors explanation (Fama (1981); Kaul, 1987; Boudoukh and Richardson, 1993; Boudoukh et al., 1994); ii) by inflation, or monetary authority response to inflation, damaging the real economy (Geske and Roll, 1983); and iii) by inflation increasing the risk-aversion of the agents (Brandt and Wang, 2003). The second approach relies on the seminal paper by Modigliani and Cohn (1979), who emphasize the aggregated errors of agents suffering from money illusion. Recent papers endorse this behavioral explanation, as the cases of Campbell and Vuolteenaho (2004); Cohen et al. (2005); Brunnermeier and Julliard (2006); and Schmeling and Schrimpf (2008). The behavioral approach is the approach receiving most of the support in the empirical literature.

Some theoretical papers have extended the friction approach. Wei

(2008) builds a Neo-Keynesian model in which the correlation of stock prices and inflation does not depend on irrationality (i.e. inflation illusion). The positive association between dividend yields and inflation can be rationalized in a dynamic general equilibrium model where no inflation illusion involved. The key point is that a negative technologic shock drives both dividends and the present value of the firm down while inflation increases as the marginal cost increases. However, empirical papers so far have not found evidence of this channel. Another contribution is from Bekaert and Engstrom (2010b), who find that the bulk of the covariance between stock and bond yield comes from the positive comovements between expected inflation and equity premium. That is to say, the equity premium is highly correlated to two proxies for time varying risk: a measure of economic uncertainty and a consumption based measure of risk aversion. This goes in line with Bekaert et al. (2009a)who suggest that high inflation coincides with periods of high risk aversion and/or economic uncertainty.

Other papers have recently emphasized inherent methodological shortcomings of the proposed methodology. In particular, Wei & Jontz (2007) and Thomas & Zhang (2007) emphasize structural instability in the VAR estimation. It was previously noticed by Campbell and Ammer (1993) that the main problem of the VAR decomposition is that the results tend to overstate the relevance of the component treated as residual. In order to control for the structural stability of the VAR I perform the following robustness tests: i) VAR lags; ii) include other variables in the VAR (i.e. interest rate). Other critiques concentrate in the way the subjective agent forecasts the stock premium. I allow agents to include in their forecasting models other dimensions (variables) of the information-space other than the risk-proxy factor. I find that there still exists a positive mispricing during the hyperinflation period. Finally, a main critique is the assumption of constant (time-invariant) parameters of the VAR estimation. In order to check if the previous results are driven by assuming constant parameters in the VAR specification I estimate a time varying parameter (TVP) VAR, following De Santis (2004) and Amisano (2005).

The paper is organized in the following way. Section 2 presents the rare-event premium in a simple two-period model. Section 3 introduces the empirical implementation of decomposing the dividend yield and the stock premium. Section 4 describes the historical case, Germany from Gold Standard to Hyperinflation. Section 5 introduces the results from the estimations. In Section 6, I test whether the rare-event premium dominates over the money illusion hypothesis. In Section 7, I perform a set of robustness checks. Section 9 concludes.

4.2 Rare-Event Premium

I present the rare-event premium in the simplest two-period problem. In this setup, agents maximize a two-period utility function depending on consumption at time t and $t+1$

$$\max\ U(c_t) + \beta E_t U(c_{t+1})$$

subject to

$$c_t = e_t - p_t \xi$$

$$c_{t+1} = e_{t+1} + x_{t+1} \xi$$

$$x_{t+1} = p_{t+1} + d_{t+1}$$

where c_t is real consumption; e_t is the environment that the agent receives in each period; ξ is the number of stocks that the agent buys in period t at the price p_t; x_t is the return of the stock, which is the sum of the stock dividend d_{t+1} and the price of the stock p_{t+1}. The first order condition for the problem is the asset pricing equation

$$p_t = E_t \left\{ \frac{U'(c_{t+1})}{U'(c_t)} (p_{t+1} + d_{t+1}) \right\}$$

There are two states of the economy: bad state with probability λ; and good state with probability $1-\lambda$. Assuming the dividend path is increasing in time, the dividend at time $t+1$ takes the following form

$$E_t d_{t+1} = \gamma(1-\lambda) d_t + \lambda \underline{d} d_t$$

where $\gamma > 1$; $0 < \lambda < 1; 0 < \underline{d} < 1$. When the economy is in the bad state $(\lambda = 1)$ then $d_{t+1} = \underline{d} d_t < d_t$. In fact, the idea is that $0 < \underline{d} << 1$ so if the economy is in the bad state, the dividends are very low in comparison to its trend. This goes in the spirit of Rietz (1988) and Barro (2006), being the bad state a catastrophic event. Even a very low probability of the bad state can alter the agent behaviour given that the potential damage to portfolio return is high.

The main assumption, as introduced in Pereira (2010), is that inflation enters in the pricing kernel as a proxy for the probability of the bad state. In this simple model, I assume that the probability of the bad state is a function of inflation, so that $\lambda(t) = f(\pi_t)$, being f such that $0 < \lambda(t) < 1$, $f'(\pi) > 0$. The higher the inflation, the higher the probability of the bad state (for simplicity). Rewriting the asset price equation we get the following expression

$$E_t(R_{t+1}) - R_t^F = E_t(R_{t+1}^e) = \frac{-COV_t\left(U'(c_{t+1}), (p_{t+1} + \gamma(1-s)d_t + s\underline{d}d_t) . \frac{1}{p_t}\right)}{U'(c_t)}$$

which again we can restate as:

$$E_t(R_{t+1}^e) = \frac{-COV_t\left(U'(c_{t+1}), \frac{p_{t+1}}{p_t}\right)}{E_t U'(c_{t+1})} +$$

$$+ \quad \frac{-\frac{(\underline{d}-\gamma)d_t}{p_t} COV_t\left(U'(c_{t+1}), s(\pi_t)\right) - \gamma COV_t\left(U'(c_{t+1}), \frac{d_t}{p_t}\right)}{E_t U'(c_{t+1})}$$

Note that $\gamma > \underline{d} > 0$, so that the term $\zeta = \frac{(\underline{d}-\gamma)d_t}{p_t} < 0$. Since the covariance in last term of the numerator depends on $\frac{d_t}{p_t}$ which is known at time t we can get rid of that term. Dividing both numerator and denominator by $U'(c_t)$, we get the expression

$$E_t(R^e_{t+1}) = \frac{-COV_t\left(m_{t+1}, \frac{p_{t+1}}{p_t}\right) - \zeta COV_t\left(m_{t+1}, s_{t+1}(\pi_t)\right)}{E_t m_{t+1}}$$

Defining $R^*_t = \frac{p_{t+1}}{p_t}$ as the ex-dividend return, the expected excess return of the asset increases if the covariance between the pricing kernel and the ex-dividend return is positive. More interestingly, since the term $\zeta < 0$ and $COV_t\left(m_{t+1}, s_{t+1}(\pi_t)\right) > 0$, then the higher the covariance the higher the demanded excess return of the asset in equilibrium. This second term is the one I identify with rare-event premium.

Dividing and multiplying by $VAR_t\left(m_{t+1}\right)$, and after some algebra, the previous expression can be written as

$$E_t(R^e_{t+1}) = \left(-\frac{VAR\left(m_{t+1}\right)}{E_t\left(m_{t+1}\right)}\right) \times$$

$$\times \left[\frac{COV\left(m_{t+1}, \frac{p_{t+1}}{p_t}\right)}{VAR(m_{t+1})} + \zeta \frac{COV\left(m_{t+1}, s_{t+1}(\pi_t)\right)}{VAR(m_{t+1})}\right]$$

where the term $\frac{VAR_t(m_{t+1})}{E_t(m_{t+1})}$ is the price of risk and the terms $\frac{COV_t\left(m_{t+1}, \frac{p_{t+1}}{p_t}\right)}{VAR_t(m_{t+1})}$ and $\frac{\zeta COV_t(m_{t+1}, s_{t+1}(\pi_t))}{VAR_t(m_{t+1})}$ are risk quantities (beta pricing model). Note that the second term in square brackets is negative, since $COV_t\left(m_{t+1}, s_{t+1}(\pi_t)\right) > 0$ and $(\underline{d} - \gamma) < 0$. When the realized inflation rate increases, the probability of the bad state in the next period also increases. Given the positive premium on rare-events, the expected stock return increases, thus the real stock price decreases.

4.3 Empirical Implementation

As in Campbell and Shiller (1988), I decompose the dividend yield into a time varying stock premium and expected dividend growth rate

$$d_{t-1} - p_{t-1} \approx \frac{k}{\rho - 1} + \sum_{j=0}^{\infty} \rho^j E_{t-1} r_{t+j}^e - \sum_{j=0}^{\infty} \rho^j E_{t-1} \triangle d_{t+j}^e \qquad (4.1)$$

where $\triangle d_{t+j}$ denotes log dividend growth, r denotes log stock return, $\triangle d_{t+j}^e$ denotes $\triangle d_{t+j}$ minus the log risk-free rate for the period, and r^e denotes r minus the log risk-free rate for the period. ρ and k are parameters of the linearization defined as $\rho \equiv 1/\left(1 + exp(\overline{d-p}\right)$ and $k \equiv -log(\rho) 1/\left(1 + exp(\overline{d-p}\right)$-(1-$\rho$)$log(1/\rho - 1)$. The differences bewteen money illusion and rare-event premium come in the treatment of the expected stock premium.

4.3.1 Stock Premium Under Money Illusion Hypothesis

Campbell and Vuolteenaho (2004) assumes the existence of two types of agents in the economy. Type S (subjective) agents suffer from money illusion, while agents type O (objective) do not. For simplicity, assume both constant real discount rates and dividend growth rates (Gordon model). In this case, the dividend price ratio can be expressed in the following manner

$$\frac{D_t}{P_{t-1}} = R^O - G^O \qquad (4.2)$$

$$\frac{D_t}{P_{t-1}} = R^S - G^S \tag{4.3}$$

where G^i stands for the dividend growth rates, and R^i is the real discount rate. Given that agents observe only one realization for the dividend-price ratio, then both valuations should be equalized

$$\frac{D_t}{P_{t-1}} = R^O - G^O = R^S - G^S \tag{4.4}$$

From Equation 1, adding and subtracting R^S , we have

$$\frac{D_t}{P_{t-1}} = -G^O + R^S + \left(R^O - R^S\right) = -G^O + R^S + \varepsilon \tag{4.5}$$

where $\varepsilon = R^O - R^S$, is a mispricing component. Adding and subtracting a risk-free interest rate in Equation 4, the dividend price ratio can be expressed as

$$\frac{D_t}{P_{t-1}} = -G^{e,O} + R^{e,S} + \varepsilon \tag{4.6}$$

where $G^{e,O}$ stands for the dividend growth rates in excess of the risk-free rate; and $R^{e,S}$ is the subjective real discount rate in excess of the risk-free rate. In order to perform the decomposition I estimate a VAR including the price-dividend ratio, the excess stock returns, the inflation rate and a proxy for the risk premium. For the equity premium proxy I use the historical volatility of the excess returns relative to that of nominal bonds as in Asness (2003)[2]. With the VAR estimated parameters I estimate $\sum_{j=0}^{\infty} \widehat{\rho^j E_{t-1}} r_{t+j}^{e,A}$. After having the expected premium, I estimate the expected excess dividend growth rate $\sum_{j=0}^{\infty} \widehat{\rho^j E_{t-1}} \triangle d_{t+j}^{e,A}$, since by Equation (1)

$$\textstyle\sum_{j=0}^{\infty} E_{t-1} \triangle d_{t+j}^{e,A} \approx p_{t-1} - d_{t-1} + \sum_{j=0}^{\infty} E_{t-1} r_{t+j}^{e,O} \tag{4.7}$$

Type S agents are assumed to use in their forecast a sub-set of the in-

[2]Campbell and Vuolteenaho (2004) use a cross-sectional beta premium from Polk, Thompson and Vuolteenaho (2004)

formation set. Following Campbell and Vuolteenaho (2004) I assume that the term $\sum_{j=0}^{\infty} E_{t-1} r_{t+j}^{e,S}$ depends on the risk factor λ_t (historical volatility of the real stock returns relative to that of real bond returns)[3]. Therefore, the type-S agent expected discount factor can be infered running an OLS regression:

$$\sum_{j=0}^{\infty} \rho^j E_{t-1} r_{t+j}^{e,S} = \alpha + \beta \lambda_t = \alpha + \beta \frac{Vol\,(r_s)}{Vol\,(r_B)} \tag{4.8}$$

With $\sum_{j=0}^{\infty} \widehat{\rho^j E_{t-1}} r_{t+j}^{e,B}$ we can get the difference between both types of agents (ψ_t),

$$d_{t-1} - p_{t-1} \approx \frac{k}{\rho - 1} + \sum_{j=0}^{\infty} \rho^j E_{t-1} r_{t+j}^{e,S} + \psi_t - \sum_{j=0}^{\infty} \rho^j E_{t-1} \triangle d_{t+j}^{e} \tag{4.9}$$

$$\hat{\psi}_t = \sum_{j=0}^{\infty} \rho^j \widehat{E_{t-1} r_{t+j}^{e,O}} - \sum_{j=0}^{\infty} \rho^j \widehat{E_{t-1} r_{t+j}^{e,S}} \tag{4.10}$$

Having the estimated mispricing component $\widehat{\psi}_t$, we regress them on the inflation rate, to check how the subjective risk premium, the expected dividend growth and the mispricing relate to the inflation.

4.3.2 Stock Premium under Rare-Event Hypothesis

As discussed in the previous section, the expected excess return can be decomposed in two terms. The first term does not depend on inflation, while the second depends positively on the previous period realized inflation:

$$\sum_{j=0}^{\infty} \rho^j E_{t-1} r_{t+j}^{e} = \sum_{j=0}^{\infty} \rho^j E_{t-1} \left(r_{t+j}^{*}\right) + \sum_{j=0}^{\infty} \rho^j E_{t-1} r \left(\pi_{t+j-1}\right)_{t+j} \tag{4.11}$$

The structure resembles the one analyzed in the previous section, but

[3]In Section 8, I relax this assumption, allowing type B agent to forecast the stock premium using any subspace of the information space.

in this case in an intertemporal approach. Also, this structure allows to follow a similar approach to the one by Campbell and Vuolteenaho (2004) and Brunnermeier and Julliard (2006). However, in their approach they decompose the observed risk premium into a subjective risk premium (independent of inflation) and a mispricing component (depending on realized inflation). In this approach, the mispricing component is understood as the rare-event premium:

$$
\begin{aligned}
d_{t-1} - p_{t-1} \approx \frac{k}{\rho - 1} + \sum_{j=0}^{\infty} \rho^j E_{t-1}\left(r^*_{t+j}\right) + \\
+ \sum_{j=0}^{\infty} \rho^j E_{t-1} r\left(\pi_{t+j-1}\right)_{t+j} - \sum_{j=0}^{\infty} \rho^j E_{t-1} \triangle d^e_{t+j} \qquad (4.12)
\end{aligned}
$$

4.3.3 Money Illusion or Rare Event Premium?

In a reduced way, both models are observationally equivalent. However, the two models present two main differences that allow us to test if one dominates over the other. First, the rare-event premium is state dependent, while money illusion is not. That is, when the economy is in the bad state, the premium should vanish. The rare-event premium, is, by construction, present in the good state of the economy. Second, the rare-event premium depends on inflation entering the expectations set as a proxy for the probability of the bad state. If inflation does not enter the investment opportunity set, then the premium should again be insignificant. The money illusion approach does not rely on inflation entering the expectational space. I use the case of Germany 1870-1935 to test these two implications, and check what approach better fits the data.

4.4 Germany Post-WWI: Reparations, Inflation, Recovery and Depression

The economic history of Germany presents a clear break after the First World War. Before 1914 the Imperial Germany had a relatively stable and limited government economy. After World War I Germany was very different. The Weimar Republic suffered revolution, insurrection, war-reparations and hyperinflation, which were part of the Great Disorder that inspired the title of Feldman's book (Feldman 1997). The situation after 1924, while better than in the previous period, still presented high volatility: post hyperinflation recovery, depression, and the pre-World War II recovery.

4.4.1 The Road to Hyperinflation

The post-war Germany was a roller coaster of social, economical and political issues. After Germany's defeat in World War I the government collapsed and a socialist style government got into office after the Kaiser abdication. The economy and the country were in shambles following the loss of the war and the new government of the Weimar Republic attempted to work its way out of the crisis. By May 1919 the terms of the Versailles Treaty became public, increasing the pressure on the government which finally resigned in June. A new government signed the Treaty as a way to buy time and reputation on the domestic and foreign sides. However, the Treaty could not mollify uncertainty about reparation expenditures and short-run government fiscal restrictions. The uncertainty increase is reflected on the inflation rate. In Figure 4.3, I plot the month on month inflation rate. Inflation increased to 6.6 percent in June 1919. The firm of the Treaty pushed inflation downwards, but by September inflation peaked at a 12 percent month on month. The French rejection to the German proposal for assisting directly in northern France reconstruction added to the foreign uncertainty and inflation rallied up to 13.9 percent by January 1920.

The government felt the pressure to pass new legislation dealing to tax-packages and other fiscal reforms. Reparations were proving to be very hard to finance if not by the Reichbank accommodative policy of monetizing government debt and fiscal deficits. From November 1919 to February 1920 the Erzberger fiscal reforms were worked and finally passed in March 1920. An example is worth in order to illustrate the kind of pressures the government was facing: while the tax package was being passed on March 12th, the Kapp Putsch[4] was taking place.

The tax reforms and the control of the putsch increased optimism. By May 1920, agents were betting for an exchange rate appreciation of the mark. The forward exchange rate data from the London exchange market posts a negative premium on the mark[5], as seen in the lower panel of Figure 4.3. Interestingly, the Reichbank intervened the exchange market in order to avoid its appreciation which was seeing as inconsistent with a policy of increasing exports in order to afford reparations. The Reichbank bought foreign currency and sold marks to maintain the high exchange rate. The optimism in the economy is translated into decreasing month on month inflation rates. In fact, from May to September 1920 inflation rates were negative.

The bad news regained momentum on the fiscal front. The tax reforms were aimed to increase total revenues but with a year lag. Thus, more debt was needed to finance the deficit. Again, optimism made people to hold domestic debt in expectation of future fiscal surpluses.

[4]In March of 1920 a right wing group, led by Wolfgang Kapp, rose in Berlin. This group consisted of members of the paramilitary Freikorps and had the support of many army officers.

[5]The data on the mark forward premium is from Einzig (1937) and is used as a proxy for expected inflation following Frenkel (1977).

Part of these surpluses were attached to the reparation schedule bargaining. It was precisely the unclear reparation schedule and the poor fiscal news what put pressure on inflation again in the last quarter of 1920.

By April 1921 the terms of the London Schedule became public. They amounted for 10 to 11 percent of the national income, or about three quarters of the export revenues[6]. The contract conditions were tough, including for example the payment of one billion goldmarks by August[7]. Inflation regained momentum in June (4.1 percent) and was 10.1 percent on average from June 1921 to May 1922 (see Figure 4.4).

For a government willing to honored the reparations, an inflationary accommodative policy seemed to be the only available resource to smooth consumption in time. The tax reforms implemented one year before under Erzberger proved to be insufficient to finance the overall increasing expenditure. In fact, while the effort was high, it proved to be insufficient. Some estimations accounted that from April 21 to June 22 reparations and similar expenses were equivalent to the overall government deficit[8]. One of the main issues was the non-indexation of tax liabilities. The higher the inflation, the lower the real revenues, thus the higher the deficit ceteris paribus.

In spite of the generalized turmoil foreign agents were still optimistic in relation to the German economy. They were still betting on the mark to revalue. The mark premium on the forward exchange rate was still negative, as seen in Figure 4.3. Webb (1989) provides an explanation for this puzling situation. The author emphasizes differences in attitudes towards risk: while risk averse locals were hedging related to local activity and trade (pressuring the mark to depreciate),

[6]SeeWebb (1989) for a detailed description of the economical implications of the London Reparation Schedule.

[7]The package included 0.5 billion goldmarks by November 15th. The 1.5 billion goldmarks accounted for almost half of total fiscal revenue.

[8]Havenstein (1922), President of the Reichbank, cited by Webb (1989).

risk neutral foreign with well diversified portfolio opportunities were betting on the mark to revalue. While this explanation seems plausible, another explanation may come from expectations on a more favourable reparation rescheduling.

The Genoa conference in May crashed the beliefs on a better treatment towards Germany, when France denied any reparation reschedule. While the Genoa conference may be thought as the crucial inflection point in the story of accommodative inflationary policy, it proved not to be so. In fact the inflation rates in May and June were at the 1921-22 average (10.6 and 9.0 percent, respectively).

The plot corresponds to the output of a Bayesian TVP VAR estimation, two lags, and 30,000 draws. For the estimation of the rare-event premium the matrices A_t were estimated using a time varying parameter Bayesian VAR estimation, following Amisano (2004). Stocks become clearly underpriced (conditional on expected discount rates and expected dividend growth rates) at the beginning of the inflationary period, and as inflation rallies without control after June 1922, stocks become overpriced. As the probability of the bad state of nature increases, so does the premium and stocks become underpriced. As the economy enters in the bad state, other effects (e.g. real debt liquefaction) dominate, creating a conditional overpricing of stocks, as discussed before. Note the sharp spike in January 1924. Once inflation is controlled, the premium goes back to be positive and high, although quickly decreases as the economy earns back credibility.

What was the main coordination device that led the agents to abandon the optimistic scenario? In Section 5, I find that the most important event was the lending indefinitely postponement decided by an American-British bankers committee leaded by J.P. Morgan. Although the decision was based on the French rejection, this proved to be the trigger of the pessimistic coordination[9]. In modern terms,

[9] Abreu and Brunnermeier (2003) present a model in which news, by enabling

we can think on the committee refusal to finance Germany either as a sovereign downgrading by a credit rating agency or a refusal to maintain assistance of a multilateral credit agency (i.e. the IMF disbursement policies in Russia 1998 or Argentina 2001). Both foreign and domestic agents understood that the policy of short-term inflationary deficit financing was doomed.

4.4.2 The Inflation Period: June 1922 - November 1923

The negative dynamics in both economical and political fronts led to the hyperinflation period. The sovereign downgrading of the American-British bankers committee did not come alone. As another example of the complexity of the political situation, foreign minister Walter Athena, who was considered a relevant player in the German-Allies negotiations, was killed by June 24th. By December the monthly growth rate of the government debt had risen to 50 percent. Inflation was above 100 percent by November, and above 50 percent in December 1922, as seen in Figure 4.4. In January 1923 France occupied the Ruhr region, and the German government encouraged a passive resistance. On a practical basis, passive resistance meant more expenditures in order to finance the zero-production of the big firms in the region.

The first serious attempt to stabilize the economy as in February, when the Reichbank took some measures with very short-term success. The inflation rate decreased in March to 7 percent compared to 136 percent in February. However, the fiscal situation was impossible to improve in the short-term. The need for foreign financial assistance was key. In April the government tried to issue gold-indexed bonds. It was a failure. Again, as with the banking committe decision to froze financing, this was used by the agents as a coordination device

synchronization, can have a disproportionate impact in the financial market relative to their intrinsic informational content.

and inflation sky-rocketed[10].

The impossibility to restraint inflation under the fiscal and political circumstances made the government and the Allies to take dramatic measures aiming to recover stability. France made public her will to make concessions if Germany recovered a stable-price scenario. In August, while the fiscal news continued to be negative, the new government announced an stabilization fiscal package. The principal measures were: a) indexing railroad rates; b) passing emergency levies; c) issuing small-denomination dollar indexed debt; d) indexing firm's tax liabilities in gold value.

The fiscal scenario was a part of the problem, but indexation created another source of inflationary inertia. If the plan was to succeed, the Reichbank assistance to the government and big firms should come to an end. Morevoer, the Reichbank authorities were even more ambitious and asked for legal autonomy in order to curtail the permanent monetisation of the government deficits.[11]. By September the government called the passive resistance to an end, allowing the restoration of diplomatic talks with France. In October 1923, the legislation on all tax indexation was passed. By the end of that month France agreed to form a new committee to discuss reparation reschedule (the root of the Dawes plan of 1924).

The Reichbank policies of government and corporate debts monetisation; public deficits monetisation; and the Notgeld currency recognition were to be ended if credibility was to be regained. The opening

[10]The daily life stories on this chaotic period are abundant: from people ordering two beers at a time because the beer would warm more slowly than the quick price adjustment (Keynes, 1923) to firms paying wages by furniture vans (Dornbusch 1987).

[11]Since September the Reichbank curtailed heavily assistance to the corporate sector by government paper discounting, which was the main source of credit by the time. This evidence somehow goes against the strong criticism to the Havenstein direction. Graham (1930) is quoted by Yeager(1981) and Dornbusch 1987 as writing of Havenstein's death as " a demise which cannot be thought of as other than opportune".

of the Rentenbank and its commitment to non-assistance of the government was its stress-test. The Reichbank pegged the papermark at 10^{12} per Rentenmark and 4.2. 10^{12} per dollar in November[12]. The attempts to stabilize the economy were finally tested in December 23rd. By then the Treasury asked the Rentenbank for further assistance. All the reforms would had failed in case of the Rentenbank accepting to finance public deficits again[13]. The strong rejection marked the regain of trust and confidence, both from domestic and foreign agents[14]. However, some authors claim that the stabilization of the economy was not a probability one event even after the adjustments took place [15].

4.4.3 Post-Inflation: Economic Recovery

On the real side, the credit squeeze that firms suffered was tremendous. While many authors have emphasized the post-hyperinflation recession (e.g. Webb 1989, and Turroni 2003), the finding in this paper suggests that the recession was not because of the stabilization but the hyperinflation itself. However, the rise in unemployment and the number of bankruptcies during the spring of 1924 were also tests for the degree of commitment of the authorities to continue the tax reforms and the non-assistance to government and corporate sectors. In Figure 4.5, the variation in annual net domestic product is plotted. While the net domestic product collapsed a 10 percent in 1923, the recovery was also a very strong 17 percent in 1924, in spite of the deceleration of the second half of the year. The post-crises real activity

[12]Dornbusch (1987) defends the role of exchange rate and interest rate policy as a necessary condition in order to establish credibility in the stabilization program.

[13]This statement is based on Sargeant (1982) in having credible fiscal stabilization as a necessary condition for the success of the program

[14]After the Rentenbank rejected to assist the Treasury, the Finance Ministry raised emergency taxes, anticipated taxes and issued gold mark bonds

[15]As an example of this, Dornbusch (1987) emphasizes the increase in corporate credit during November- December. The Rentenbank multiplied four times the credit to corporations during this period.

rebounds in economies without access to credit is analysed in Calvo et al. (2006) for Latin American countries. The case seems to apply also to post-hyperinflation Germany.

The Dawes plan approval in August 1924, which granted a substantial reduction of the German reparations payments, together with the election defeat of radical parties in December 1924, were the key events that consolidated the German recovery. From January to December 1925 real stock prices increased steadily. Other political events at the time were the October 1925 Treaty of Locarno that scaled back some allied rights under the Treaty of Versailles, and Germany's membership in the League of Nations beginning in September 1926. All these events reinforced confidence in the German economy in such a way that during 1926 Germany increasingly attracted capital inflows, both short and long-term flows[16], mainly explained by higher interest rates than in the United States and Britain (see Voth 2003). The stock market rebound between December 1925 and April 1927 was really strong, more than 160 percent in real terms over a period of eighteen months.

While stock prices peaked in mid 1927, German's economic activity peaked in 1927-28, starting its way to the depression. The German depression started before the US 1929 crash, making of the German case a well studied one. Schmidt (1923) and Landes (1969) emphasize the role of capital inflows as a cause of the depression while Temin (1971) establishes a fall in domestic demand as the main cause. On the domestic side, Weder (2006b) studies the depression in a general equilibrium framework using a sequence of sunspot realizations, while Weder (2006a) explains the depression by a sequence of negative taste innovations starting in 1928. Voth (2003) emphasizes the role of the Reichbank intervention in May 1927. The strong and quick recovery made the Reichbank to tackle a perceived bubble in

[16]Temin (1971) establishes a fall in domestic demand as the main cause of the German Depression.

the German stock market.

4.5 Estimation and Results

4.5.1 Data

For the stock yield decomposition a VAR estimation is performed. The variables included in the estimations are the dividend-price (in logs), the excess stock returns, the inflation rate and a set of factors that proxy for the risk premium. The stock market return data is from Gielen (1994). Gielen works with information from various sources to construct dividend-adjusted series for 1870-1993[17]. The series for risk free rate corresponds to the discount rate for loans to banks and is from Global Financial Data. Following Asness (2003), I use for the proxy of risk premium the historic volatility of the stock market over the volatility of a government bond yield. In this case, I use the same government bond rate as the one consider for the risk-free rate. I use the previous twelve-month volatility in order to calculate the ratio used as proxy for the stock premium. With respect to inflation, I work with both month on month inflation rate and year on year inflation rates. During the study I define a dummy variable in order to identify hyperinflation periods. This dummy takes value of one between June 1922 and November 1923[18]. I also consider the expected inflation implicit in the forward exchange rate. The London forward exchange rate premium is from Einzig (1937). The data starts in May 1920 and the market closes in August 1923.

4.5.2 VAR Estimation

In order to perform the dividend yield decomposition I estimate a

[17]See Bittlingmayer (1998) for Gielen's data description.

[18]Note that I adopt a conservative criterion. For example, Dornbusch (1987) defines hyperinflation periods as those in which inflation grows between 15-20 percent or more.

VAR including the variables excess return, stock premium, dividend yield and inflation. The VAR is then expressed in companion form as

$$X_t = AX_{t-1} + v_t$$

where A is the coefficient matrix to be estimated and the vector $X = (r_s^e, rp, dp, \pi)$, being r_s^e stock excess return, rp stock premium, dp dividend yield and π inflation rate[19]

The optimal lag specification is three when using the month on month inflation according to SBIC criteria. In order to test for the presence of unit roots in the residuals I perform Augmented Dickey Fuller, Philips Perron and the efficient unit root tests from Elliot et al (1996) and Elliot (1999)[20]. Each test has been run with a null hypothesis of unit root against the alternative of trend stationarity. All the tests reject the presence of unit root. Finally, I also perform tests for the null of trend stationarity against the alternative of a unit root (KPSS test), in which case I can not reject stationarity. However, all tests reject normality of residuals.

4.5.3 Expected Inflation: VAR Forecast vs Forward Exchange Market

Before discussing the dividing yield decompositon results, I use the output from the VAR estimation to compare the forecasted inflation to an expected inflation proxy coming from the forward exchange rate premium (see Frankel, 1977). I use a proxy for expected inflation using data from the London forward exchange market. The data from the forward exchange rate premium is from Einzig (1937). I compare foreign agent[21] inflation expectations with the expected inflation rate

[19] For robustness, in Section 7, I include the risk-free interest rate in the endogenous variable vector.

[20] The last set of tests have shown to be much more powerful than the standard unit root tests, particularly against stationary but highly persistent alternatives such as long memory or nonlinear processes.

[21] By foreign agents I refer to agents trading in foreign markets.

coming from the estimated VAR. It is worth to emphasize that the marginal investor may not the same, so the expectation space may differ. In fact, Webb (1989) emphasizes differences between domestic agents and foreign agents that could explain different behaviour and expectations in the foreign and domestic markets. However, the evidence shows that both domestic and foreign agents expectations were actually similar. In Figure 4.7, I plot the series for the period July 1920 to October 1923. The correlation is as high as 0.94 for the period, while the standard deviation for the foreign market is higher than the expected inflation infered from the VAR (1.36 vs 1.14, respectively). The forecasted inflation from the VAR estimation follows closely those expectations implied in the forward exchange rate market, giving a ground base for the results discussed below.

4.5.4 Stock Premium

Following Campbell and Shiller (1989), I get the long-term expected stock premium ($\widehat{\sum_{j=0}^{\infty} \rho^j E_{t-1} r_{t+j}^{e,obj}}$) using the matrix of estimated coefficients from the VAR,

$$\sum \rho^{j-1} E_{t-1} r_{t+j}^{e,obj} = e_2' \rho A (I - \rho A)^{-1} X_t \tag{4.13}$$

where e_2=$[1,0,0,0]$, A is the matrix of estimated coefficients, I is the identity matrix and X_t is the vector of dependent variables as described above. For the estimation I use a coefficient $\rho = 0.999$. A high stock premium is usually associated with high risk aversion or high volatility periods, as seen in Figure 4.9. The different economic and financial crises experienced by Germany during the period are identifiable, although the variations are minimized by the hyperinflation spike[22].

[22]When using year on year inflation the early 1890's slowdown and the WWI spikes are clearly identifiable. Using the month on month inflation rate highest peak corresponds to the hyperinflation period, while when using the year on year inflation rate the peaks of 1870s, 1890s WWI, and the hyperinflation are very sim-

Since most of the variation takes place after the WWI period, in the second panel of Figure 4.10 the focus is on the period 1913-1926. While in this specification WWI does not seem to affect the expected premium, after the war ends we observe a decrease in the premium. The stock premium remains low until February 1920, when it increases coinciding with the inflation acceleration. After July 1921, while inflation rates turn negative the premium decreases, and remain below average for most of the months until July 1922. Coinciding with the American-British bank committee denial for further foreign assistance the the stock premium increases, presenting a local maximum by December 1922. After that, and coinciding with the stabilization attempts in early 1923, the premium fluctuates around the mean during the first months of 1923, and finally spikes from July until November 1923, as does inflation. After the stabilization the premium decreases strongly, however the second half of 1924 shows a couple of spikes. These spikes relate to the post-hyperinflation crises during the second half of the year.

In Table 4.3, I present the results from regressing the estimated stock premium on monthly inflation. In the specification I include a dummy for the hyperinflation period and cross-term of inflation times the hyper dummy. For the stock premium, higher inflation is associated with an increase in the stock premium. This relation tends to disappear during hyperinflation periods, since the coefficient is not different from zero. However, the dummy variable for the hyperinflation period shows a significant and negative coefficient. During this period, stocks become relatively more attractive. One possible reason for this effect is that stocks are backed by real capital, while bonds are completely nominal promises. As inflation decreases, the bond value decreases independently of the default probability. Thus, stock premium decreases.

ilar in magnitude.

4.5.5 Expected Dividend Growth Rate

The long-run expected excess dividend growth ($\sum \rho^j E_{t-1} \triangle d_{t+j}^{e,obj}$) is recovered using Equation (7). I plot the deviation of the excess long-run expected dividend growth rate from its unconditional mean in Figure 4.8. Expected dividend growth rates are relatively stable during the period 1880-1910 compared to the period 1914-1935. All major economic downturns are present in the plot: the crises of 1870s and 1890s are clearly identifiable in the figure. After WWI, agents were confident in a fast and strong recovery of the big German corporations. The spike by the end of the war is showing precisely the expectations of very high dividend growth rates. However, this proved to be short lived as post-war Germany was a roller coaster of social, economical and political issues as: government resignations, peace treaty negotiations, and radical group putsches[23]. The consequence is the high volatility of the expected dividend growth rate. However, note that the expected dividend trend is also upwards. The way to reconcile both increasing volatility and upward trend of expected dividend growth rates is by understanding the government and the central bank policies. While inflation increased, the Reichbank was actively backing the corporate sector with credit. This policy helps to explain the increase in the expected dividend growth rate from the end of 1920 up to its peak in August 1922.

At the beginning of the uncontrolled inflation period, and up to mid-1923, the expected dividend growth rate remained to be very high. While inflation was tearing apart the economy, the corporate sector (big firms traded in the market) was surging. This can be summarized in the following quotation coming from a financial review (Plutus, July 1923): “There have been extraordinary rises in the quotations for all shares, the chief cause being the catastrophic change in the economic situation”. The policies of negative real interest rates,

[23]Feldman (1993) refers to this period as the “Great Disorder”.

the explicit insurance of the Reichbank by lending money without restrictions to the corporate sector and, more importantly, the optimism of the agents in the future path of the economy (the Mark was expected to appreciate as seen in Figure 4.3 and 4.4) were the key elements explaining the increase in the expected dividend growth rate.

By May-June 1922 the banking-committee sovereign downgrading increased pressure on the government and its inflationary accommodative policies. However, the expected dividend growth rate level remained high until May 1923. In spite of agents becoming more pessimistic, the explicit insurance of the Reichbank and the inflationary effects on domestic input costs were avoiding a collapse in the expected dividend growth rates for the traded firms.

The long-run expected dividend growth rate decreases heavily after May 1923 and reaches a trough that coincides with the hyperinflation peak in November 1923. The main policies that stabilized the economy were: stop fiscal deficit financing; the indexation of big firms' tax liabilities; the impossibility to access the Reichbank rediscount window; the indexation of loans to gold-marks; and the changes in accounting rules (gold-backed balance sheets).

As soon as inflation decreased and the political turmoil was contained, expected dividend growth turned positive again. After the hyperinflation period, expected dividend growth returned to pre-hyper period rates[24]. These strong expected rates remain high for three months, but after April 1924 it shows a strong decrease, reaching a trough by December 1924. This corresponds to the post-hyperinflation crisis discussed in Webb and Turroni (2003). After December 1924 the expected dividend growth rates recover strongly again, reaching a post-recover peak takes place in March 1927. After this peak the expected dividend rate started to fall up to the depression trough in the early thirties.

[24]The credit-less recoveries after economic slumps is documented in Calvo et a (2004)

It is worth to relate these results to the historical literature. For the hyperinflation period, the literature has associated the economic contraction to the stabilization measures. The evidence posted here shows that the collapse started before the inflation came to be under controlled. Second, stock-investors were optimistic until mid 1923 in relation to the future dividend growth rate. The failure in issuing gold-backed bonds was the final coordination device that made the easy-credit/negative-real-interest-rate policy to disappear from agents' expectations. Third, expected dividend growth rate was not higher in 1927 than in pre-collapse period, or the immediate post-war period. Therefore, there is no evidence of overpricing in the sense of unusually high expected dividend growth rates. This piece of evidence reinforces Voth (2003) in the sense of showing that the monetary authorities did not have hard evidence pointing in the direction of a bubble existence by 1927. Finally, the Reichbank intervention in May 1927 undoubtedly affected the long-run expectations of the agents, but these were already decreasing before the intervention. Thus, is difficult from this evidence to conclude that the intervention actually was the inflection event that led the way to the 30's crisis as in Voth (2003). Actually, March 1927 seems to be the true inflection point[25].

The negative correlation between inflation and expected dividend growth deserves particular attention. In Table 4.3, I present the results from regressing the long-term expected dividend growth on inflation. Expected dividend growth rate is negatively correlated with inflation. During normal times, an increase in inflation makes agents to expect lower future real dividend growth rates. For the hyperinflation period the overall effect of inflation is statistically not different from zero. However, the dummy variable is significant and negative, implying a

[25]Other explanations are Weder (2006b), who identifies a sequence of negative shocks to expectations attributing the lion share of the period volatility to sunspots; while Weder (2006a) uses a DSGE model to identify a sequence of negative preference shocks.

decrease above 20 percent in real terms (annualized terms). This result also holds for Emerging Markets, as discussed in Pereira (2011).

4.5.6 Stock Premium Decomposition

After analysing the relation between inflation and both long-run expected stock premium and long-run expected dividend growth rate, now I decompose the stock premium in two components. As discussed above, the first component depends linearly on the relative volatility of the stock market returns with respect to bond returns. The second component, the rare-event premium, comes as the difference between the estimated stock premium and the relative volatility of the stock market returns with respect to bond returns. This last component is the one that Campbell and Vuolteenaho (2004) and Brunnermeier and Julliard (2006) understand as a mispricing factor related to money illusion.

The rare-event premium (or mispricing component) is plotted in Figure 4.9. The results show a strong decrease in the rare-event premium, or mispricing during the hyperinflation period[26]. Thus, agents tend to overprice stocks conditional on expected dividend growth rates and subjective stock premium during the hyperinflation period[27]. After inflation is stabilized, the rare-event premium, or the overpricing decreases[28].

The econometric results included in Table 4.4 show that during normal times inflation correlates positively with the rare-event premium (or mispricing component), while during the hyperinflation period the effect is statistically null. This evidence confirms the results of Campbell and Vuolteenaho (2004) for the US since the authors find that higher inflation is significantly related with underpricing.

[26]The observed effect is much stronger when using month on month inflation.

[27]I find similar results for Argentina, Brazil and Mexico.

[28]It is worth noting that during the depression stocks were also overpriced according to this methodology.

The higher the inflation, the lower the subjective valuation, in line with the Modigliani-Cohn inflation illusion hypothesis[29]. However, this relation is not linear: when facing very high inflation agents tend to overvalue stocks, which is at odds with the behavioural approach.

In Figure 4.10, I plot the expected dividend growth rate and the rare-event premium taking as $T = 0$ the trough of the expected dividend growth rate. I identify five crises previous to the hyperinflation period. These troughs take place during the years 1877, 1882, 1890, 1897 and 1916. In the upper panel of Figure 4.10, I plot the average for these five crises, from T-6 to T+6 months. Agents underprice stocks while the expected dividend growth rate decreases, since both series comove. That is, conditional on expected dividend growth rate and the subjective stock premium agents underprice stocks. The opposite happens during the hyperinflation crisis as shown in the lower panel of Figure 4.10. Agents tend to overprice stocks as the expected dividend growth rate collapses.

What are the factors driving the real stock over-pricing during hyperinflation periods? One explanation deals with equity playing the role of an insurance against the bad state of nature. During periods of very high inflation (increasing expected inflation) nominal assets tend to be rationally less valuable than other asset involving a real claim. In particular, stocks are claims on the firms real capital (e.g machines, physical plants). While the probability of a total financial market disruption is high, the value (in the form of an insurance) of a claim on real capital tends to increase (the insurance is more expensive while the probability of the bad estate of nature increases). Therefore, when facing portfolio optimization agents would be inclined to increase the relative participation of stocks in relation to domestic bonds or banking deposits. While the nature of the first relates its value to physical capital, nominal bonds and banking deposits are generally

[29]Pereira-Garmendia (2008) finds evidence supporting Modigliani-Cohn negative correlation for Brazil, but not for Argentina and Mexico.

purely nominal contracts that pay a fix nominal amount. During that period high inflation may decrease the real value of the contract to very low values. The exception would be either bonds or deposits linked to inflation, or bonds and deposits in foreign currency[30].

This evidence also goes in line with the flight into real-assets story (see Webb 1989, chapter 5). When facing expectations of future increasing inflation agents tend to hold real claims, like equities, rather than normal claims, like bonds. This story may rely on incomplete markets, since agents can create hedging strategies[31]. In the case of Germany, markets as the real state market of the foreign currency markets were heavily restricted. In particular, price controls in the real state market were astonishingly disruptive[32].

4.6 Is It Rare Event Premium or Money Illusion?

There are two cases that would help to differentiate the rare-event premium from money illusion. First, the rare-event premium is state-dependent while money illusion is not. Second, inflation must be included in the expectations set for the rare-event premium to make sense, while this is not true for money illusion approach. First, the rare-event premium is state-dependent. When the economy is in normal times, agents demand a premium for a potential bad state of nature. However, when the economy is in the bad state, the premium should vanish. On the other side, the behavioral approach, in particular money illusion, is not state dependent. There are a number

[30]Note that the definition of the risk premium (risk of investing in stocks) only takes into account bonds and stocks in domestic currency, and not any other asset denominated in foreign currency.

[31]Pereira-Garmendia (2008) finds stock overpricing even in cases with much less restrictions on the agents portfolios.

[32]However, Pereira-Garmendia (2008) shows that portfolio constraints are not a sufficient condition for the existence of overpricing. In fact, in Argentina during the 80s and 90s agents were able to have dollares (in foreign currency or foreign currency denominated deposits).

of articles in which the presence of money illusion is tested in high inflation regimes. For example, Shafir, Diamond and Tversky (1997) claim that “residues of money illusion are observed even in highly inflationary environments”. Moreover, Fisher (1928) provides several interesting examples of inflation illusion during very high inflation periods, to be more precise during the German Hyperinflation[33]. I test the strength of this argument by using the hyperinflation period in Germany as the bad state of the economy. I find that for normal times, inflation correlates positively with risk premium, and that relation vanishes during the hyperinflation. This goes in line with the rare-event premium and against the money illusion hypothesis.

Second, the main assumption behind the rare-event approach is that agents update the probability of the bad state using realized inflation rates. On the other side, the behavioral explanations point to inflation level as the driver of agent mistakes. I can test which of the two approaches is more grounded by using the role of inflation on expectations. If the agent does not incorporate the inflation rate when updating then the rare-event premium should vanish. As discussed below, the Gold Standard period presents two defined sub-periods, which are useful to test whether it is the rare-event premium or money illusion what drives the correlation. Again, I find evidence in favor of the rare-event premium and against the money illusion hypothesis.

4.6.1 State Dependency

Markov switching models are a good tool to analyze the impact of inflation on the peso-risk premium. I run a 2-state Markov switching regression between the rare-event premium (mispricing component) and monthly inflation rates. I allow for two states:

[33]For example on pages 6-7 Fisher writes about a conversation he had with a German shop woman during the German hyperinflation period in the 1920s: “That shirt I sold you will cost me just as much to replace as I am charging you [...] But I have made a profit on that shirt because I bought it for less.”

$$p(y_t \mid s_t) = N\left(x_t'\beta_{st}, h_{st}^{-1}\right)$$

$$p(s_t = j \mid s_{t-1} = i, \underline{s}_{t-2}, \underline{y}_{t-1}, \underline{x}_{t-1}) = p(s_t = j \mid s_{t-1} = i) = p_{ij}$$

$$P = \begin{bmatrix} p_{11} & 1-p_{11} \\ 1-p_{22} & p_{22} \end{bmatrix}$$

for $i, j = 1, 2$. Table 4.6 includes the results from estimating the model. In State 1 (the good state), the mean for the estimated coefficient is negative, and significantly different from zero. In State 2 (which coincides with the inflation period) the mean for the estimated coefficient is positive but not significantly different from zero. Also, as expected, the variance in state 2 is almost ten times the variance of the good state, while the constant is capturing the overprice during the inflation period, being one order higher than the constant in the good state. During the good state of the economy, higher inflation correlates negatively with the stock mispricing (positively with the peso-risk premium). In the bad state of the economy (probability one for the hyper period), the correlation between inflation and the peso-risk premium is positive but not significant, although the constant is capturing the overpricing in this state. Inflation is not incorporating relevant information during the bad state of the economy.

An interesting fact coming from the estimation is that the bad state of the economy remained with probability close to one until the second half of 1924. This coincides with the literature describing high uncertainty even after inflation became under control (cf Dornbusch (1987), Turroni (2003), Webb (1989)).

4.6.2 Inflation not Included in Investment Set

Inflation expectations should be a factor in the pricing kernel, in this case as a proxy for the probability of the bad state of nature instead of the expected dividend growth proxy of Fama (1981). A good test for the peso risk reinterpretation is to analyze the correlation between inflation and the mispricing component during the Gold Standard period (1890-1910 in this sample). The Gold Standard period presented two clear phases: the deflationary one (1870-1895); and the 'inflationary' one (1895-1910). These phases were determined by gold production. As money supply was tightened to gold reserves, the increase of gold production caused an increase in price levels. During this period, real economic growth causes inflation, which (following Fama (1981) proxy hypothesis) induces higher stock prices. However, when analyzing the whole Gold Standard period, Barsky and DeLong (1991) show that the price changes during the 1879-1913 period in US were never built into inflation expectations. In either case, if the rare-event premium interpretation is correct, we should find either a positive or a null correlation between inflation and the rare-event premium during the Gold Standard Period, and a negative correlation after that.

The results from regressing the mispricing component on inflation are in Table 4.7. There are four periods in the table: Gold Standard period (1870-1910); the non-inflationary Gold Standard subperiod (1870-1895); the inflationary Gold Standard subperiod (1895-1910); and the non Gold Standard period (1926-1940). For the complete Gold Standard period (1870-1910) inflation presents a negative but non-significant coefficient. For the non-inflationary Gold Standard subperiod (1870-1895) inflation has a negative and significant coefficient. This means that an increase in the inflation rate induces a decrease in the stock premium. Note that this is strictly the opposite of the inflation illusion hypothesis. The inflationary subperiod (1895-1910), posts a positive but non-significant coefficient. For this period there was not a relation between inflation and changes in the bad-states of the economy probabilities. Inflation was not a relevant factor in the agents' pricing kernel. This is intuitive given the passive monetary policy followed under the Gold Standard system. In Figure 4.13, I plot the estimated coefficient for inflation from a rolling window regression. Coherent with the results in Table 4.7, the coefficient starts as negative and significant, and from 1890 it becomes not significantly different from zero. Finally, the regression for the post-Gold Standard Period (starting in 1926) posts a positive and significant coefficient for inflation. Variations in the inflation rate relate to the state probabilities, and therefore affect equilibrium prices and returns.

The results from the Gold Standard Period confirm that the relation between risk aversion and inflation is better explained by the rare-event explanation than by the behavioual money illusion as suggested by Modigliani and Cohn (1979).

4.7 Robustness

Some papers have emphasized inherent methodological shortcomings in relation to the way in which agents infer the expected discount rates. Wei and Jontz (2007) and Thomas and Zhang (2007) emphasize structural instability in the VAR estimation[34]. For example, after controlling for structural change, Wei & Jontz (2007) find no evidence of inflation illusion for the post-1952 period in US.

In order to test if the VAR specification or other assumptions are driving the results, I perform the following robustness tests: i) VAR lags; ii) include other variables in the VAR (e.g. interest rates).

A second critique comes from the assumption of constant (time-invariant) parameters of the VAR estimation. In order to test if the previous results are driven by assuming constant parameters in the VAR specification I estimate a time varying parameter (TVP) VAR[35].

[34]It was previously noticed by Campbell and Ammer (1993) that the main problem of the VAR decomposition is that the results tend to overstate the relevance of the component treated as residual

[35]I follow De Santis (2004) and Amisano and Federico (2005). In this paper I

Finally, other critiques concentrate in the way the subjective agent forecasts the stock premium. To test if this assumption is driving the results, I allow agents to include in their forecasting models other dimensions (variables) of the information-space other than the risk-proxy factor.

4.7.1 Standard VAR Estimation Robustness

I perform the following robustness tests: i) VAR lags; ii) include other variables in the VAR (in particular the risk-free interest rate). The first test is to run the VARs with the optimal lags according to different criteria. In all cases the results presented in the previous sections hold. I do not present all the tests for the sake of space. With respect to the second point, as discussed in Chen and Zhao (2008), the inclusion of different variables in the information set of the agents may lead to different results. In order to test if the inclusion of more variables in the VAR may create significant changes in the estimated long-run real discount rate, I performed the estimations including the risk-free interest rate as another dimension of the information set. Again, the results presented in the previous sections hold.

4.7.2 Error-Space and Rare-Event Premium

In Section 4, I introduced an agent who repeats consistently the same mistake in time. That is, she does not take into account the whole information space to forecast the stock premium. So far we only took into account the relation between the historical volatility of the stock return relative to that of government bond market (variable λ_t)

$$\sum_{j=0}^{\infty} \rho^j E_{t-1} r_{t+j}^{e,obj} = \alpha + \beta \lambda_t + \psi_t \tag{4.14}$$

perform a bayesian TVP estimation. See Canova (2008) for bayesian VARs and time varying parameter bayesian VARs; Primiceri (2005) and Amisano and Federico (2005).

This assumption may be driving the results for the rare-event premium. To make sure this is not the case, I repeat the estimation of this factor as the difference between the forecast of an agent using all information set dimensions and this agent restricted to only one dimension (λ_t). I relax this assumption by allowing the agent to make her forecasts using different models (information set dimensions), except the complete information space since then she would be the same as our rational agent.

I create seven[36] different ways in which the irrational agent is able to forecast the stock premium. The different models to infer the stock premium take into account inflation, dividend-price and excess stock returns (in addition to the relation between the historical volatility of the stock return relative to that of nominal government bonds). Using the errors coming from the regressions I create an error-space which basis set is the space of the seven error-series (see Appendix I). I rotate this basis using principal components in order for one basis-vector to maximize the explained volatility. The vector that maximizes the explained volatility in the data is the one corresponding to the highest eigenvalue of the variance-covariance matrix of the spanned-space. After having the new basis I create the time series for the corresponding first and second principal components using the corresponding loadings.

In Table 4.8, I present the results from regressing the first and second principal components on inflation. The first principal component seems to be the one explaining most of the action, since it explains 59 percent of the common variance. Inflation correlates positively with the first principal component during normal times, and the correlation vanishes during the hyperinflation period. The second principal component (which explains 29 percent of the common

[36]Nothing prevents me from estimating a n-dimensional space (n>7). I introduce this seven-dimensional error space as different papers forecast expected returns using these dimensions. Incorporating more dimensions do not change the results.

variance) only experiences a positive intercept jump during the hyperinflation period, and no correlation with inflation. In Figure 4.13, the first principal component is plotted, while the the shaded area corresponds to the hyperinflation period. The first principal component experiences a jump during the hyperinflation period in line with the mispricing component behaviour analyzed before[37]. Hence, we can be confident that the overpricing during this period does not come from the specific forecasting procedure used in Section 3.

4.7.3 Time-Varying-Parameter VAR Estimation

One main criticism to the previous evidence is that the estimated parameters of the VAR may not be constant in time. Structural change may be a problem, in particular during very volatile subperiods (as hyperinflations or financial crises). Timmermann (2001) finds empirical evidence on the existence of multiple structural breaks in the U.S. monthly dividend process. Evans (1998) uses Campbell and Shiller (1988) decomposition allowing for the dividend process to switch between two regimes. De Santis (2004) argues that discrete switching models either impose a finite number of recurring states, or a finite number of non-recurring states and the switch between regimes is a discrete jump. Instead he models the joint distribution of the variables of interest as a VAR with time varying parameters. This is the strategy I perform in order to check if the evidence found in the previous sections is just the outcome of restricting the estimated parameters to be constant in time.

The model of the joint distribution of excess stock returns, stock premium, dividend-price ratio and inflation, in that order, as a VAR with time-varying parameters:

[37] I repeat the exercise calculating five-year loadings in order to control for loading-changes in time. The results are very close for the first principal component in Figure 4.13.

$$y_t = X_t' \theta_t + u_t$$

$$X_t' = I_n \otimes \left[1, y_{t-1}'\right]$$

where y_t includes the variables described before, $\otimes$ denotes the Kronecker product, and θ_t is the $k \times 1$ vector of time varying coefficients (latent variables).

The cost of avoiding the finite number of states of the discrete switching models is to impose a set of strong assumptions. Since the latent variables are now assumed to be continuous, in order to make the filtering analytically feasible, we need to implement the following assumptions: Gaussianity and linearity of the law of motion of the latent variables θ_t [38]

$$u_t \sim N(0, H^{\varepsilon\varepsilon})$$

$$\theta_t = A\theta_{t-1} + v_t$$

$$v_t \sim N(0, H^{\eta\eta})$$

$$VAR \begin{pmatrix} \varepsilon_t \\ \eta \end{pmatrix} = H^{-1} = \begin{bmatrix} H^{\varepsilon\varepsilon} & 0 \\ 0 & H^{\eta\eta} \end{bmatrix}$$

By estimating the TVP VAR parameters θ_t (which plays the role of matrix A of Section 3 for each t), I can repeat the same long run forecast procedure that in Section 3.2 in order to get the estimated long-run dividend growth rate and the stock premium. The long run estimation changes in time, as the parameters in A change for each t.

In Figure 4.14, I plot the results for the estimation of the rare-event premium. Note that there are not significant differences with the results discussed in previous sections. Stocks become clearly underpriced (conditional on expected discount rates and expected dividend growth rates) at the beginning of the inflationary period, and

[38] See Amisano and Federico (2005) for a comprehensive discussion on the topic

as inflation rallies without control after June 1922, stocks become overpriced. As the probability of the bad state of nature increases, so does the premium and stocks become underpriced. As the economy enters in the bad state, other effects (e.g. real debt liquefaction) dominate, creating a conditional overpricing of stocks, as discussed before. Note the sharp spike in January 1924. Once inflation is controlled, the premium goes back to be positive and high, although quickly decreases as the economy earns back credibility.

4.8 Discussion and Conclusions

In this paper I use a historical case of Germany 1870-1935 to show that it is the rare-event premium, not money illusion, what drives the negative relation between inflation and stock prices, conditional on expected dividend growth rates. I find evidence supporting the rare-event premium, and against the money illusion hypothesis.

There are two cases that help to differentiate the rare-event premium from money illusion. First, the rare-event premium is state-dependent. When the economy is in normal times, agents demand a premium for a potential bad state of nature. However, when the economy is already in the bad state, the premium must vanish. On the other side, the behavioral approach, in particular money illusion, is not state dependent[39]. I test the strength of this argument by using the hyperinflation period in Germany as the bad state of the economy. I find that for normal times, inflation correlates positively with risk premium, and that relation vanishes during the hyperinflation. During the bad state (hyperinflation period), agents tend to overprice stocks conditional on expected long-run discount rates and expected

[39]There is controversy on this statement. However, most papers in Behavioral Finance find at least 'residuals' of money illusion in very high inflation episodes.

long-run dividend growth rates.

While in this paper I do not offer a definite explanation for the conditional stock overpricing in the bad state of nature, I suggest two different channels: a) that stocks may play the role of protective puts for portfolios that include assets which returns are nominally determined; and b) a real debt liquefaction channel. Since the value of the firm is equivalent to the debt and stock capitalization, as the former has seniority, an unexpected inflation increase reduces the debt value. Controlling for the expected dividend growth rate and stock premium, the residual claimer increases her share value as debt value goes to zero. This effect may be also driving the results as in this framework this effect should show up in the mispricing component. Future research is needed to disentangle which effect is present, or which one is more important.

The second test that helps to differentiate the rare-event premium from money illusion is done for the Gold Standard Period. The main assumption behind the rare-event approach is that agents update the probability of the bad state using realized inflation rates. On the other side, the behavioral explanations point to inflation level as the driver of agent mistakes. I test which of the two approaches is more grounded by using the role of inflation on expectations. If the agent does not incorporate the inflation rate at least when forecasting future inflation then the rare-event premium explanation does not stand. The Gold Standard period presents two well defined sub-periods, which are useful to test whether it is the rare-event premium or money illusion what drives the correlation. As before, I find evidence in favor of the rare-event premium and against the money illusion hypothesis.

I follow Campbell and Vuolteenaho (2004) and Brunnermeier and Julliard (2006), in decomposing the dividend yield in three components: long-run expected dividend growth rates; long-run expected discount rates; and a money illusion related residual. The decomposition is based on the Campbell and Shiller (1989) vector autogression (VAR) approach.

I present robustness tests to prevent the case of the results coming from VAR misspecifications. I test the VAR lags; the VAR specification and I also estimate a time varying parameter VAR. The evidence from the different procedures backs the results of the base specification. I also perform a robustness test for how the subjective agent forecasts the long-run discount rate.

While in the base specification the subjective agent uses only the stock premium proxy (variance of the stock return compared to variance of the bond yield) to estimate the expected long-run stock premium, I allow for different forecast models. I create an error space, which I decompose in its principal component vector base, and find how the first and second principal component correlates with inflation. Again, I find that the first principal component of this space (explains almost 60 percent of the common variance) correlates positively with inflation during the hyperinflation period.

Table 4.1: Catastrophic Events

Notes: Data from Barro and Ursua (2008). Note that most hyperinflation catastrophic events are not included in the sample due to lack of data. *. Average Barro-Ursúa (2009) sample. **. Finland, Germany, Greece, Italy, Argentina, Brazil, Chile, Peru. *** Germany, Argentina, Brazil, Chile, Peru. **** Inflation higher than 50 percent year on year: Iceland, Argentina, Chile, Mexico.

	GDP	**Consumption**
Full Sample*	-17.10%	-19.30%
Non-War Related	-13.10%	-14.50%
Hyperinflations**	-25.70%	-27.30%
Non-War Related***	-17.70%	-19.40%
Very-High Inflations****	-14.60%	-12.40%

TABLE 4.2. Real Stock Market Returns and Inflation

Notes: The table presents the results from regressing monthly real stock returns on inflation. *Inflation* denotes month on month inflation (s.a. adjusted); *Hyper* is a dummy variable taking value one if the monthly inflation is above 50%, from June 1922 to November 1923. $Inflation * Hyper$ is the interaction term between *Inflation* and *Hyper* variables. Newey and West (1987) t-statistics between brackets. $R2$ is the adjusted R squared. N denotes the number of observations. ***,**, and * denote significance at the 1, 5 and 10%, respectively.

	(i)	(ii)
Inflation	-0.005***	-0.004***
	(-31.883)	(-16.395)
Inflation*Hyper		-0.002***
		(-3.966)
Hyper		-0.141***
		(-2.777)
Constant	-0.016	-0.013
	(-1.570)	(-1.600)
R2	0.186	0.242
N	817	817

Table 4.3: Expected Dividend Growth and Stock Premium

Notes: The dependent variable is the estimated long-run expected dividend growth, calculated from as the long-run expectation from the reduced VAR $x_t = Ax_{t-1} + \nu_t$, where A is the coefficient matrix to be estimated and the vector $x_t = (Er_t, RP_t, DP_t, \pi_t)$, being excess return, stock premium, dividend yield and inflation. $Inflation$ denotes month on month inflation (s.a. adjusted); $Hyper$ is a dummy variable taking value one if the monthly inflation is above 50%, from June 1922 to November 1923. $Inflation * Hyper$ is the interaction term between $Inflation$ and $Hyper$ variables. Newey and West (1987) t-statistics between brackets. $R2$ is the adjusted R squared. N denotes the number of observations. ***,**, and * denote significance at the 1, 5 and 10%, respectively.

	Dividend Growth	Stock Premium
Inflation	-0.113***	0.019*
	(-4.783)	(1.950)
Inflation*Hyper	0.114***	-0.020**
	(4.811)	(-2.023)
Hyper	-0.019***	-0.011**
	(-3.539)	(-2.013)
Constant	0.001	0.000
	(0.660)	(1.047)
R2	0.298	0.603
N	817	817

TABLE 4.4: Historical Stock Premium and Rare-Event Premium

Notes: In the first column, the dependent variables are the historical stock premium measured as the relative volatility of stock market to bond market returns, vol(Rs)/vol(Rb), as in Asness 2003. Rs stands for stock market returns, and Rb for bond market returns. In the second columnm the dependent variable is the rare-event premium, which is the difference between the estimated stock premium and the relative volatility of the stock market returns with respect to bond returns. *Inflation* denotes month on month inflation (s.a. adjusted); *Hyper* is a dummy variable taking value one if the monthly inflation is above 50%, from June 1922 to November 1923. $Inflation * Hyper$ is the interaction term between *Inflation* and *Hyper* variables. Newey and West (1987) t-statistics between brackets. $R2$ is the adjusted R squared. N denotes the number of observations. ***,**, and * denote significance at the 1, 5 and 10%, respectively.

	Stock Premium* (vol(Rs)/vol(Rb))	Rare Event Premium / Mispricing
Inflation	-0.009	0.028***
	(-1.359)	(2.764)
Inflation*Hyper	0.009	-0.029***
	(1.359)	(-2.834)
Hyper	-0.002***	-0.009
	(-5.701)	(-1.601)
Constant	0.000	0.000*
	(0.478)	(1.692)
R2	0.010	0.686
N	817	817

TABLE 4.5: Inflation and Rare-Event Premium: Markov Switching Model

	Good State	Bad State
Constant (Mean)	-0.0004	-0.0042
Inflation (Mean)	0.0968	-0.003
Inflation (Standard Deviation)	0.0184	0.0686
Confidence Interval(95%)	(0.0985; 0.09529)	(-0.0060; 0.0065)

TABLE 4.6: Inflation and Rare-Event Premium During Gold Standard Period

Notes: The dependent variable is the rare-event premium component. There are four regressions, depending each on the period used for the estimation: Gold Standard period (1870-1910); the non-inflationary Gold Standard subperiod (1870-1895); the inflationary Gold Standard subperiod (1895-1910); and the non Gold Standard period (1926-1940). *Inflation* stands for month on month inflation rate. Newey and West (1987) t-statistics between brackets. $R2$ is the adjusted R squared. N denotes the number of observations. ***,**, and * denote significance at the 1, 5 and 10%, respectively.

	1870-1910	1870-1895	1895-1910	1926-1940
Inflation	-0.053**	-0.070***	0.006	0.105**
	(-2.208)	(-2.869)	(0.146)	(2.376)
Constant	0.000	0.001**	-0.001***	-0.010***
	(0.490)	(2.039)	(-2.621)	(-11.377)
R2	0.012	0.019	0.005	0.019
N	468	277	190	167

TABLE 4.7: Rare-Event Premium Space

Notes: The dependent variables are the first and second principal component of the rare-event premium space. The error-space is created using the mispricing components coming from eight different ways to forecast the stock premium (see Appendix for more details). $Inflation$ denotes month on month inflation (s.a. adjusted); $Hyper$ is a dummy variable taking value one if the monthly inflation is above 50%, from June 1922 to November 1923. $Inflation * Hyper$ is the interaction term between $Inflation$ and $Hyper$ variables. Newey and West (1987) t-statistics between brackets. $R2$ is the adjusted R squared. N denotes the number of observations. ***,**, and * denote significance at the 1, 5 and 10%, respectively.

	First PC	Second PC
Inflation	1.768**	-0.178
	(2.06)	(-0.42)
Inflation*Hyper	-1.771**	0.178
	(-2.06)	(0.42)
Hyper	0.186	0.153**
	(1.35)	(2.34)
Constant	-0.0114	-0.00226
	(-0.46)	(-0.35)
R2	0.0350	0.0948
N	753	753
Percentage of Variance	0.59	0.29

Figure 4.1: ***Real Stock Index 1870-1940***

Data from Gielen (1994). Main post World War I social, political and economic events are included.

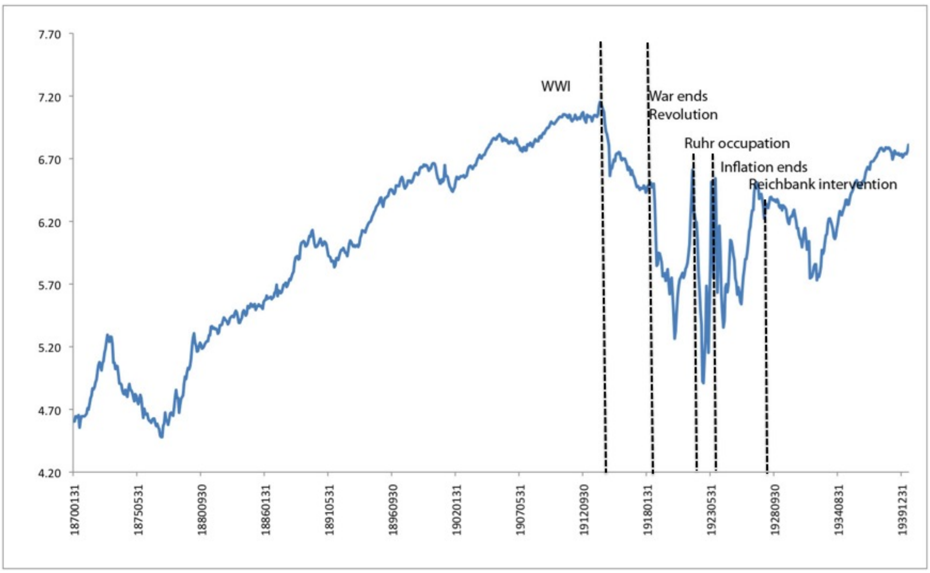


Figure 4.2: **The Road to Hyperinflation: 1918-1921**

The upper figure shows the month on month inflation rate. The lower figure shows the mark premium in the London forward exchange rate market. Note that in this case the initial period is May 1920. The data on the mark forward premium is from Einzig (1937). A negative premium indicates expected appreciation of the exchange rate vis-a-vis the pound.

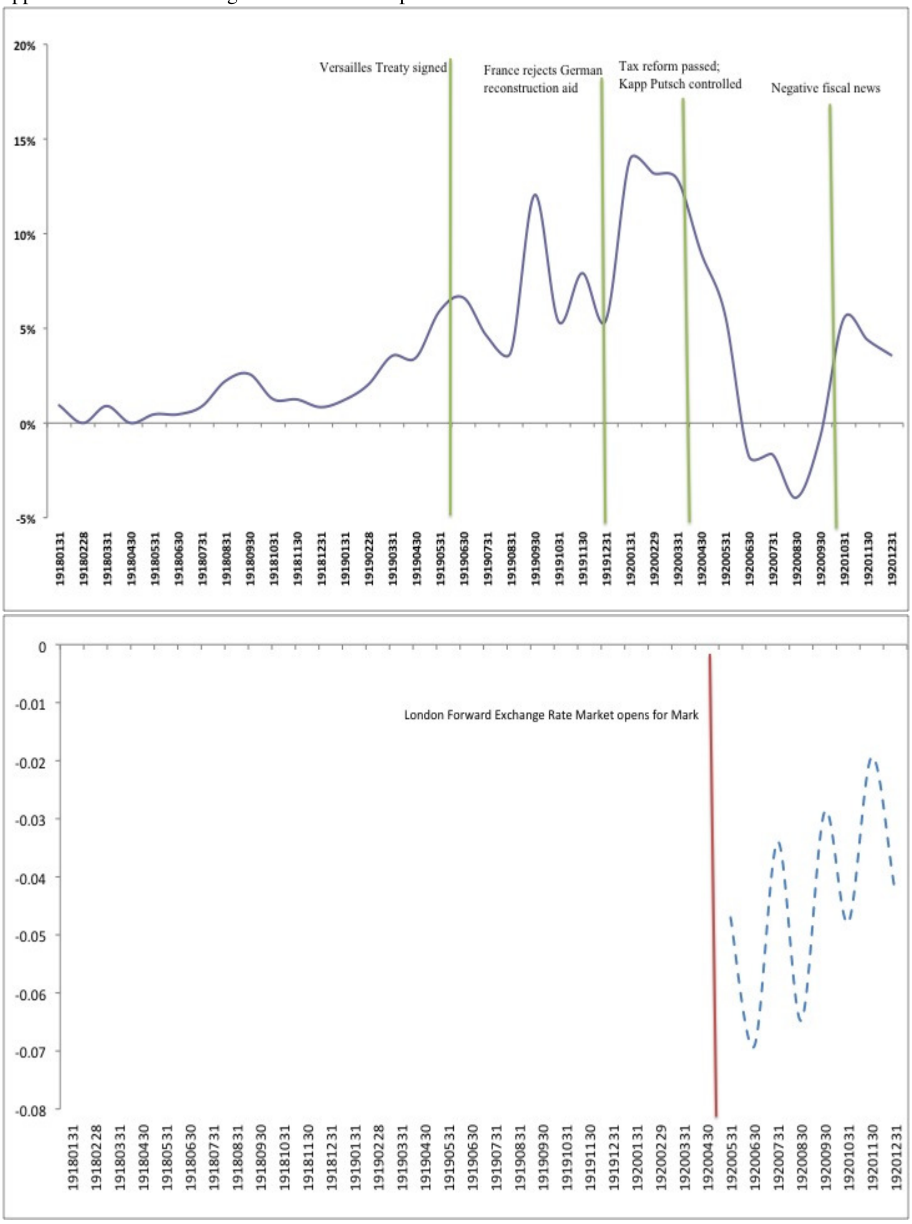


Figure 4.3: **The Hyperinflation Period: June 1922- November 1923**

The upper figure shows the month on month inflation rate. The lower figure shows the mark premium in the London forward exchange rate market. Note that in this case the last period is August 1923. The data is from Einzig (1937). A positive premium indicates expected depreciation of the exchange rate vis-a-vis the pound.

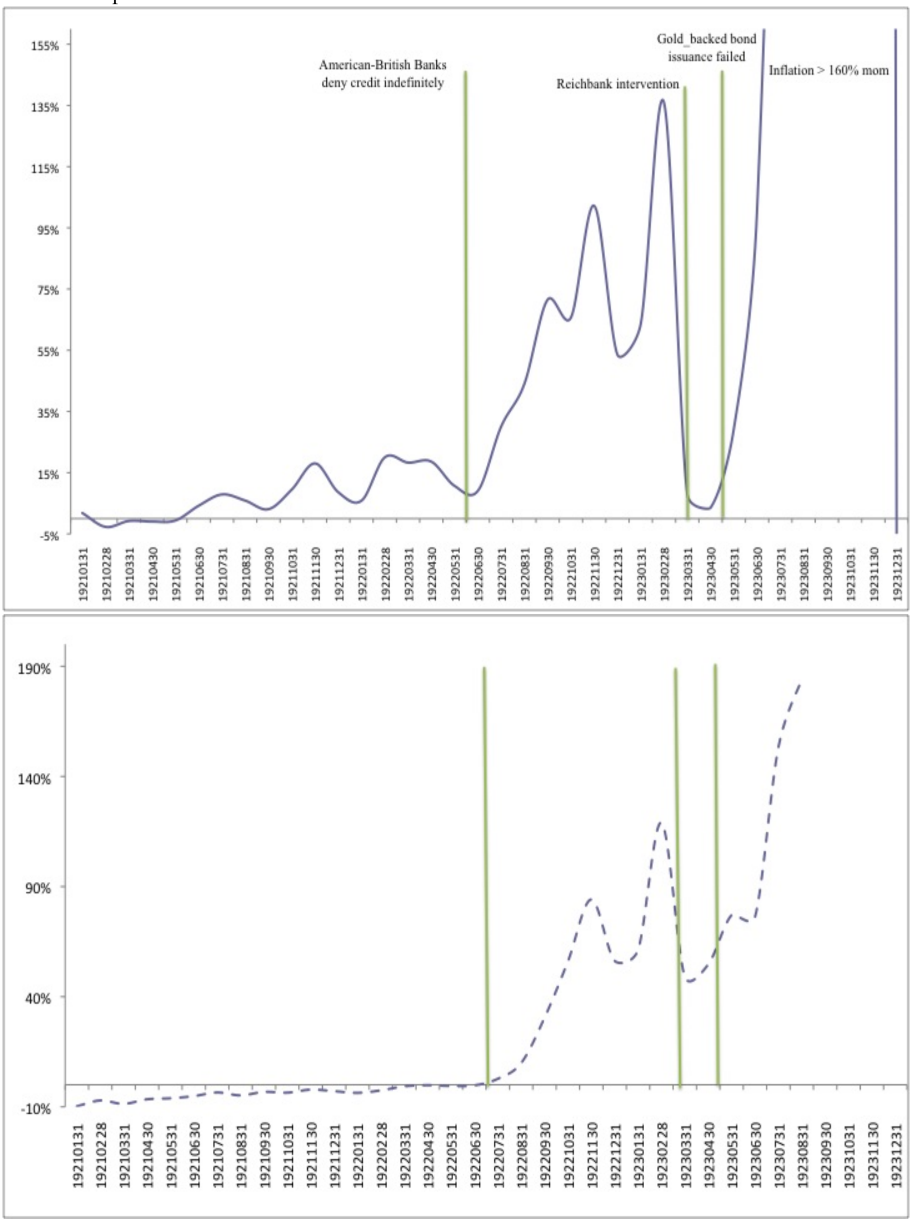


Figure 4.4: **Net Domestic Product Variation (billion marks 1913 prices)**

The source is Webb (1989), Chapter 5, pg 76. Based on Witt 1974 and Hoffmann 1965.

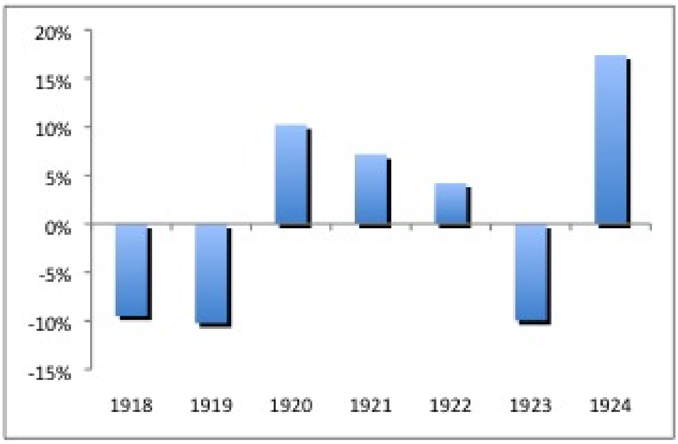


Figure 4.5: **Germany Data**

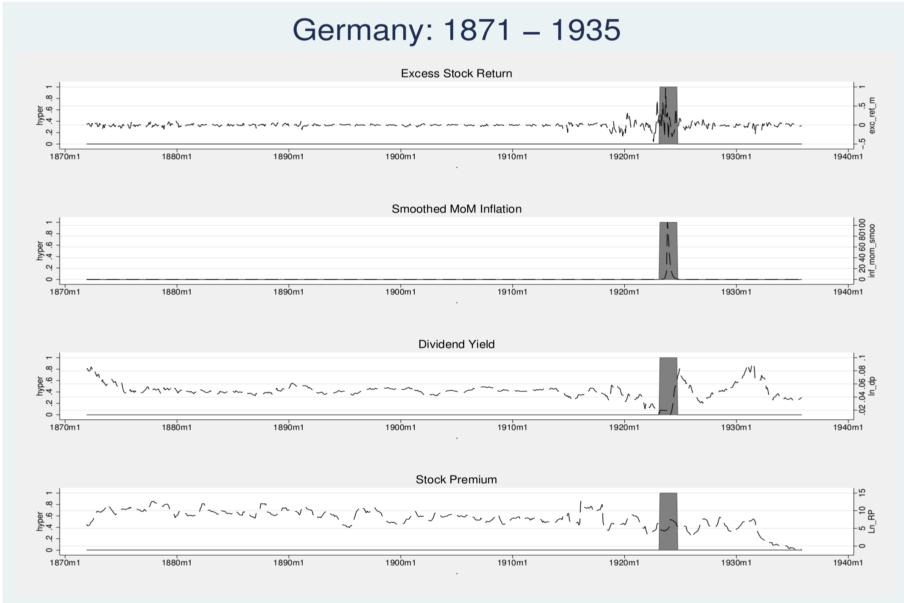


Figure 4.6: **Expected Inflation: London Forward Exchange Market and VAR Forecast**

The figure shows the month on month expected inflation rate (in percentage points) from the estimated VAR (dotted blue line) and the expected inflation calculated from the forward exchange market in London (solid red line) following Frenkel (1977). On the vertical axis, 1 equals to 100 bps.

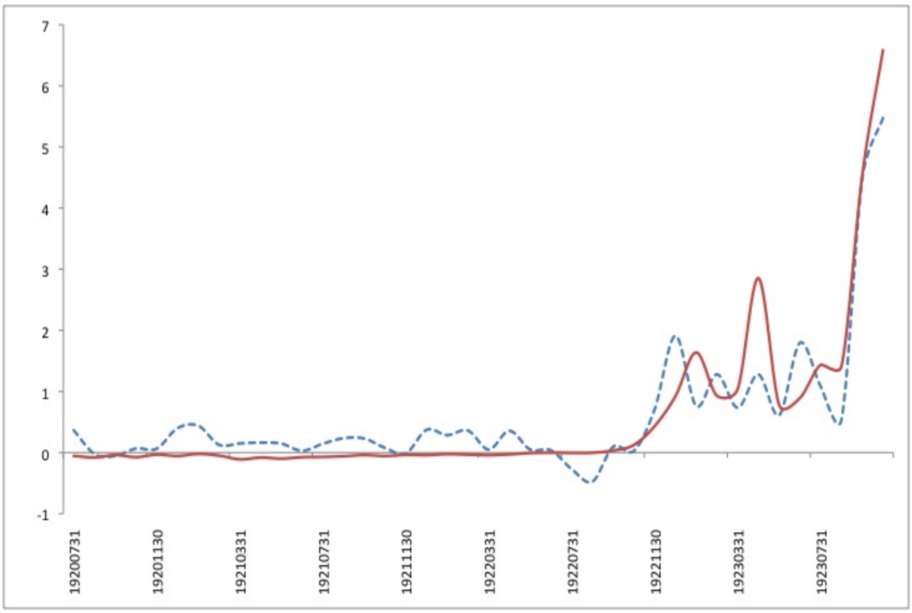


Figure 4.7: **Stock premium**

The figures plot the time-series for the demeaned objective risk-premium. For the upper figure month on month inflation rate is used to perform the estimations, while the for lower figure year on year inflation rate is used. The series are computed using the VAR results. The shaded area corresponds to the hyperinflation period (June 1922-November 1923).

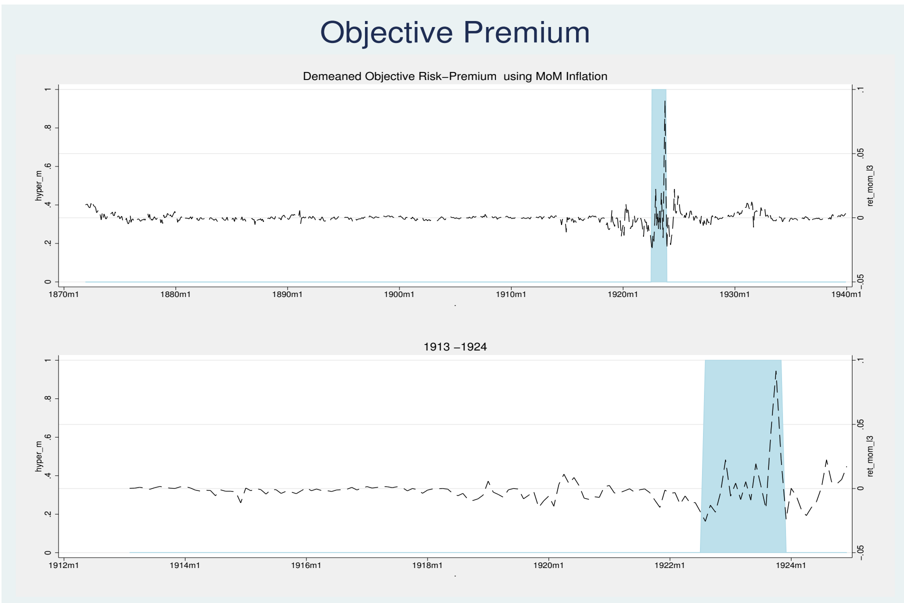


Figure 4.8: **Expected Long-run Dividend Growth Rate**

The figures plot the time-series for the deviation of the long-run expected excess dividend growth from it's unconditional mean. For the upper figure month on month inflation rate is used to perform the estimations, while the for lower figure year on year inflation rate is used. The series are computed using the VAR results. The shaded area corresponds to the hyperinflation period (June 1922-November 1923).

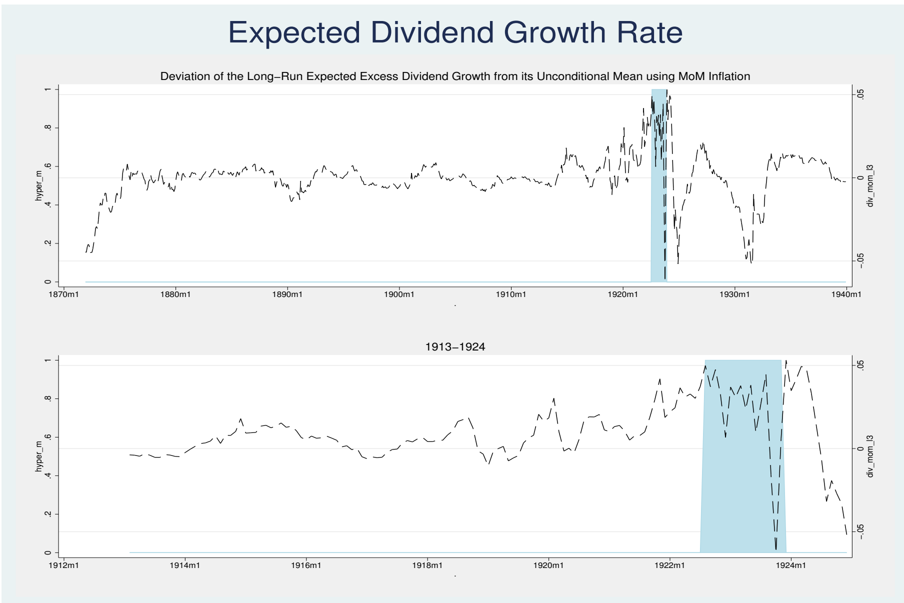


Figure 4.9: **Rare-Event Premium**

The figures plot the time-series for the mispricing component (the inverse of the component peso-risk premium). The mispricing component is estimated using regressing the discounted sum of future expected returns on the subjective risk-premium proxy. The mispricing component is the error term of this regression. For the upper figure month on month inflation rate is used to perform the estimations, while the for lower figure year on year inflation rate is used. The series are computed using the VAR results. The shaded area corresponds to the hyperinflation period (June 1922-November 1923).

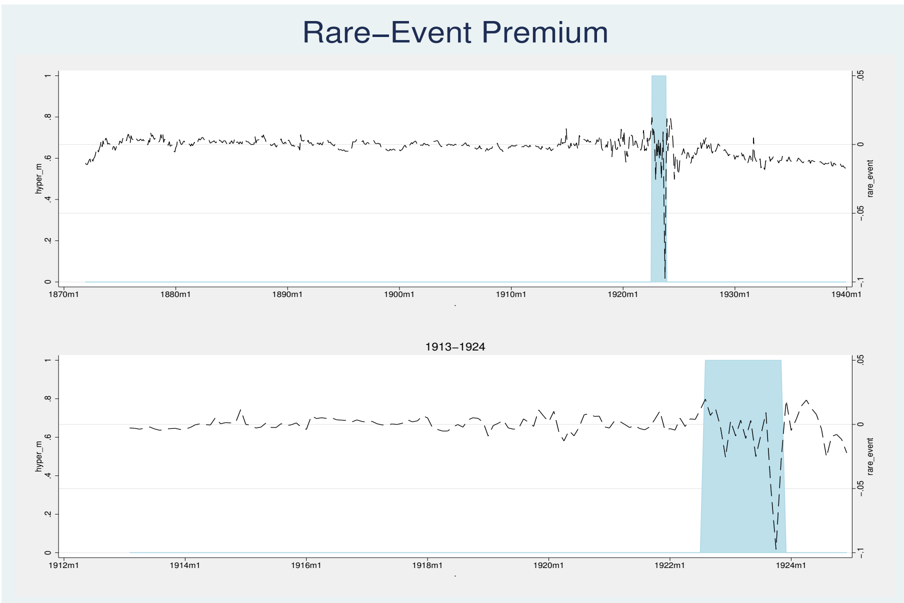
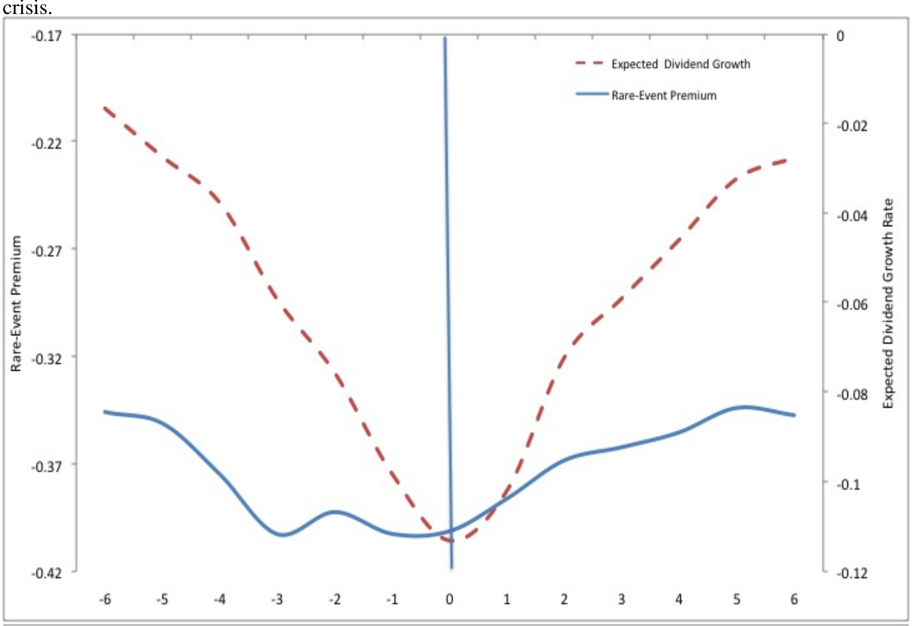


Figure 4.10: **Expected Dividend Growth Rate and Rare-Event Premium**

The figures plot the time-series averages for the deviation of the long-run expected excess dividend growth from it's unconditional mean (dotted red line) and the mispricing component (solid blue line) during different economic/financial crises. Period T=0 corresponds to the expected dividend trough during the period. The plot extends from T-6 to T+6. In the upper panel I include the averages for the crisis of 1877, 1882, 1890, 1897 and 1916. In the lower panel I include only the 1923 hyperinflation crisis.



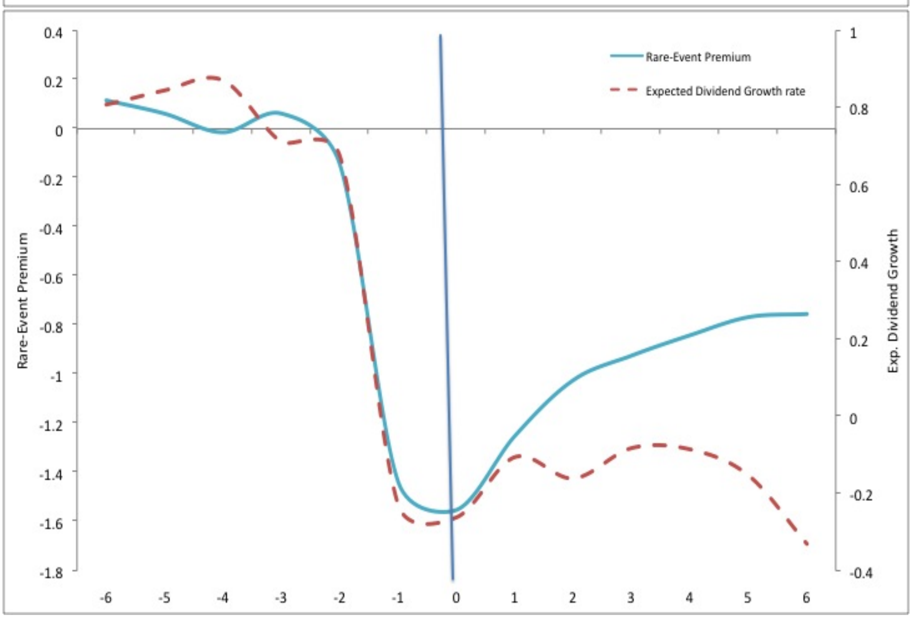


Figure 4.11: **Probability of the Bad State and Inflation**

The figure plots the probability of the bad state of the economy (in red) and the month on month inflation rate (in blue).

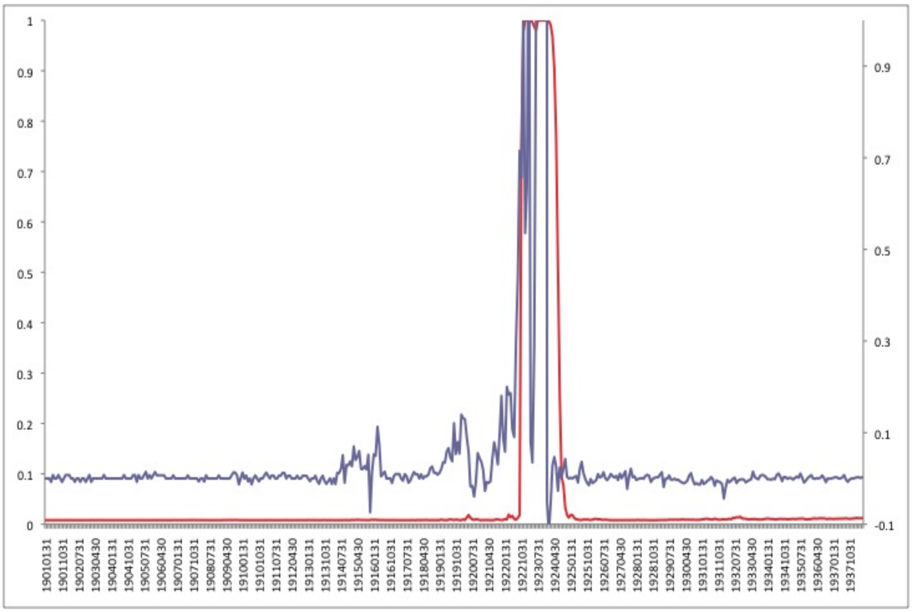
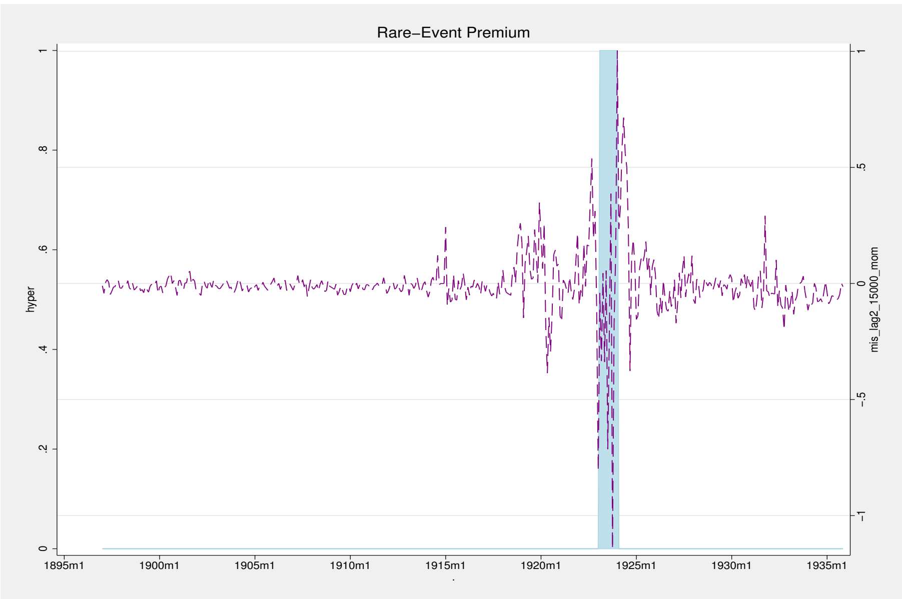


Figure 4.12: Rolling Estimation

The figure shows the estimated inflation coefficient (solid thick blue curve). Coherent with the results in Table 7, the coefficient starts as negative and significant, and from 1890 it becomes not significantly different from zero. Finally, the regression for the post-Gold Standard Period (starting in 1926) posts a positive and significant coefficient for inflation.

Figure 4.13: Rare-Event Premium (TVP VAR Estimation)

The plot corresponds to the output of a Bayesian TVP VAR estimation, two lags, and 30,000 draws. For the estimation of the rare-event premium the matrices A_t were estimated using a time varying parameter Bayesian VAR estimation, following Amisano (2004). Stocks become clearly underpriced (conditional on expected discount rates and expected dividend growth rates) at the beginning of the inflationary period, and as inflation rallies without control after June 1922, stocks become overpriced. As the probability of the bad state of nature increases, so does the premium and stocks become underpriced. As the economy enters in the bad state, other effects (e.g. real debt liquefaction) dominate, creating a conditional overpricing of stocks, as discussed before. Note the sharp spike in January 1924. Once inflation is controlled, the premium goes back to be positive and high, although quickly decreases as the economy earns back credibility.



5 US Cold, Worldwide Pneumonia: American Fama-French Factors Drive Contagion

5.1 Introduction

Many papers have studied Emerging Market (EM) contagion assuming as given an initial shock in one emerging country, and then digging to understand how the shock propagates to other emerging countries. For example, in the last period of systemic EM financial distress in 2002, the initial shock was charged on Brazil[1]. By April 2002, coinciding with the first polls showing Ignacio Lula Da Silva as favorite to win the Brazilian office, emerging markets started to witness a demolishing increase in their sovereign and private debt costs. Bond yields increased, debt rollover issues emerged, and default probabilities increased. These issues propagated to almost all emerging countries, in a clear case of what the literature has denominated contagion[2] (see Figure 5.1 and Table 5.1).

The idea of Brazil's political risk as the main cause of contagion can be seriously disputed. I use other fix-income asset classes, as the US corporate (USC) bonds, to show that they also experienced a dramatic increase in spreads at the same time EM spreads started to rally. Moreover, when corporate spreads reached their relative peak in October 2002, EM spreads also reached their relative peak (see

[1] Argentina, Ecuador, and Turkey had experienced several idiosyncratic problems before Brazil, including sovereign defaults as in the case Ecuador (1999) and Argentina (2002), though none of these events put the wheels of contagion in action.

[2] Asian countries seem to have suffered much less than other countries, with Korea actually experiencing a decrease in it's debt spreads.

Figure 5.2)[3]. Finally, after the distress period, both series show a dramatic decrease in spreads, taking emerging spreads to historical lows. The 1998 Russian crisis was the other event in the sample that showed pervasive and extended contagion. If we again consider the USC bond market, the same pattern emerges from the data on spreads (see Figure 5.3). Thus, in the last two systemic EM financial crises, the increase in comovement between the EM and USC bond spreads is observed, irrespectively of the US Corporate bond ratings.

The main contribution of this paper is to show that the US stochastic discount factor (*SDF*) is behind the increase in comovement of EM sovereign debt spreads and US corporate spreads. In other words, EMs are not good for portfolio diversification during developed market turmoil periods. I use the American Fama-French factors to proxy for the US *SDF* (e.g. the agents expectations on the investment set). I test the American Fama-French factors as determinants of EM sovereign debt spreads, thus, as contagion drivers among emerging countries[4].

The literature has stressed the importance of global risk aversion or global investment appetite[5] as a determinant of EM sovereign spreads. In fact, Calvo (2003) suggests that once we account for the fact that sovereign spreads are highly correlated with investors' appetite for risk, domestic factors are almost irrelevant in explaining sovereign spreads. The author coined the term "Globalization Hazard" in order to refer to the EM vulnerability coming from global capital market shocks (ie: the more the EM is integrated into the

[3]In a note published by the Financial Times in October 2002, Calvo and Talvi stressed the correlation between US corporate spreads and Emerging Market sovereign debt spreads during 2002.

[4]To be more precise, it is the American Fama French-based stochastic discount factor driving EM sovereign spreads and EM contagion. In the rest of the paper I will refer to the US stochastic discount factor although it should be clear that I am using the American Fama French factors to proxy for it.

[5]Global investment appetite (or risk aversion) accounts for non risk-neutral agents and for time-varying risk aversion.

global financial system, the more exposed it is to shocks originated in foreign markets). Usually, the way the literature incorporates this fact is by taking into account the spread of the US High Yield bonds as a proxy for Global Investment Appetite, and so as one of the determinants of emerging market spreads (see Dungey et al. 2004, García-Herrero and Ortiz 2005 and González-Rozada and Yeyati 2008).

This paper aims to understand the factors driving global investment appetite. The flight to quality story states that when emerging countries are in crisis, investors reallocate their portfolios to less risky assets, as for example are AAA corporate bonds. Nevertheless, these asset prices correlate positively with EM debt prices. Thus, the flight to quality story does not seem to fit the evidence. My story is that a change in agent's expectations in developed markets make them to reallocate their portfolios. This reallocation affects all risky assets, both developed and emerging countries stocks and bonds. If an emerging country is vulnerable to a decrease in capital flows (as an outcome of international portfolio reallocation), then it might experience a financial crisis (e.g. current account crisis, currency crisis, banking crisis, or a mixture of the previous). In this case, an EM financial crisis would work as a feedback device, increasing the aversion to these markets[6].

Emerging Market contagion, e.g. systemic EM financial crises, coincide with volatility spikes in US agent expectations. In this paper contagion is understood as a significant increase in the cross market correlation during a period of turmoil, not explained by fundamentals, with emphasis on the financial channel (i.e. I am not considering contagion coming from trade linkages, etc)[7]. Kaminsky et al. (2003) argue that for a contagion case to happen, one must observe surprise

[6]Financial microstructure issues like herding or margin calls aim to explain this phenomena.

[7]For theoretical works on contagion see Massen (1997), Valdes (1996), Mullainthan (1998), Calvo and Mendoza (1999).

announcements, an abrupt reversal in capital flows and the presence of a leveraged common creditor[8]. The presence of a common lender is implicit in my approach, as is a previous period of over-exposure to EM risk by US agents, implying periods of high capital flows to these countries.

A relevant share of the variance of EM asset returns can be explained by the American Fama-French factors. First, I show that the Fama-French factors are significant in order to explain EM spreads (EMBI+, aggregated index and for a thirteen country portfolio). I also follow González-Rozada and Yeyati (2008) and perform a Panel Error Correction Model (PECM) in order to disentangle long and short-run relations. Again, the Fama-French factors are significant in order to explain EM spread deviations from its long run path. Second, taking profit from the high correlation of EM spread series, I show that the first principal component for emerging markets EMBI+ and for USC bond spreads are highly explained by the American Fama-French factors. Third, I extend the analysis to other EM assets, in particular stock markets, and show that for stock market returns the US Fama-French factors are again significant and highly explicative, although these markets are in general not as integrated as the sovereign debt ones that are taken into account for the EMBI indices.

The factors used to proxy for the US stochastic discount factor are the American Fama-French factors (Fama and French (1992, 1993)). These factors are the excess return of the aggregated or market portfolio (MKT), the return of a portfolio long in high book-to-market value stocks and short in low book-to-market value stocks (HML) and the return of a portfolio long in small stocks and short in big stocks (SMB). Fama and French (1993) suggest that HML and SMB proxy

[8]Note that exposure might come from the EM itself to capital outflows. Countries might develop macro or micro mismatches (ie: domestic liability dollarization or high current account deficits) based on expectations of capital inflows to remain high and stable over medium to long-run periods. These mismatches increase the vulnerability of these markets to a decrease in capital inflows

for state variables that describe the variation in time of the investment opportunity set, with goes in line with the Intertemporal Capital Asset Pricing Model (ICAPM) developed by Merton (1973). Petkova (2006) shows that the Fama French factors HML and SMB are actually correlated with innovations in variables that describe the investment opportunity sets. She includes as state variables the short term T-bill, the aggregate dividend yield, the term spread and the default spread, in order to take into account the yield curve and the conditional distribution of the asset returns. See that the Fama French factors should be understood not as factors by themselves, but as proxies for innovations in variables that are in fact predictors of the returns.

The initial works on the determinants of EM sovereign spreads[9] discuss mainly the relevance of domestic factors. They only include the US interest rate as an external factor (short and long run rates, FED or US government rates). External factors began to gain importance as EMs returned to international financial markets by the beginning of the nineties. The external factors can be classified as: factors that proxy for volatility (Arora and Cerisola 2001, Grandes 2007, Dungey et al. 2004, González-Rozada and Yeyati 2008); factors that proxy for international liquidity (Ferrucci 2004, Dungey et al. 2004, Sløk and Kennedy 2004); factors that proxy for credit risk (Dungey et al. 2004, McGuire and Schrijvers 2003).

Another branch of the literature deals with contagion, that is, how the crises spread around the globe to different and maybe macro-fundamental unconnected countries. Contagion literature on EMs started after the Mexican crisis in 1994, when some countries without fundamentals linked to the epicenter of the crisis showed signs of distress (ie: Mexico 1994 and Argentina 1995).

The works of Grandes (2007), McGuire and Schrijvers (2003), Sløk and Kennedy (2004) and Fuentes and Godoy (2005), among

[9]See Edwards (1986), Fernandez-Arias (1996), Cline and Barnes (1997), Min (1998) and Eichengreen and Mody (1998).

others, use a different methodological approach in order to exploit the high correlation posted by the EM spread series. Since the first principal component is the vector that explains the higher proportion of the series common variance, they relate it to global risk aversion or investment appetite factor. This common factor accounts for one third of the total variation in spread changes. Maybe the most interesting work is the one of Sløk and Kennedy (2004), who analyze the synchronized nature of the changes across asset categories and national borders that occurred after the financial distress climax in October 2002. They regress the common factor (defined as a variance explained weighted average of the first two principal components) on general economic fundamentals and OECD-wide liquidity. I will follow this methodology, and I will associate the first principal component of an Emerging Market sample with global risk aversion or appetite, and test the significance of the US agent expectations on this vector.

Previously I have referred to the US stochastic discount factor (SDF) as the aggregation of US agents individual discount factors. Xiong and Yan (2009) show that in an integrated market with heterogeneous agents, the stochastic discount factor (SDF) is a weighted average of the agents SDFs. Under logarithmic utility functions, these weights are their relative individual wealth ratios. Because of this wealth shares, if the two agents are the US and an EM country, the relative incidence of the US stochastic discount factor should be the dominant one.

The paper is organized as follows. Section 2 presents the analysis for the EM sovereign debt spreads using only the US Fama French factors as determinants of the spreads. Section 3 describes the results on the relation between the first principal component time series, associated with global investment appetite or risk aversion, and the US Fama-French factors. In Section 4, I follow Petkova (2006) in using innovations on variables that can forecast future returns to proxy for the US stochastic discount factor. Section 5 extends the analysis to EM stock markets; and finally, in Section 6, I perform formal asset-pricing model specification tests where only the external factors are taken into account in order to explain sovereign debt returns. Section 7 concludes.

5.2 EM Spreads, American Fama-French Factors and Contagion

The main objective of this paper is to show that US agent expectations on future discount rates (US stochastic discount factor) drive EM sovereign spreads. To test this hypothesis I use the American Fama-French factors to proxy for the US stochastic discount factor[10]. For the EM sovereign spreads I use the J.P. Morgan EMBI+ spread series[11]. I work with the spread series in differences to avoid non-stationarity econometric issues[12].

In subsection 2.1, the results of regressing EM spreads in differences on the American Fama-French factors are reported. In subsection 2.2, I follow Gonzalez and Levy (2006) in performing a Panel Error Correction Model (PECM). The aim is to disentangle long and short-run paths, and test the relevance of the American Fama-French factors in the short-run deviations, associated with the contagion times.

[10]Campbell et al (2006) disaggregate the CAPM beta on a good beta (coming from innovations on future discount rates) and bad beta (coming from innovations on future payoffs). This paper works only with the innovations on expected discount rates, taking for given the future payoffs.

[11]This spread measures the difference between the yield on a dollar-denominated bond issued by an EM government and a corresponding one issued by the US Treasury.

[12] The spread series are found to be non-stationary for the period 1998-2006

5.2.1 EM Spreads and American Fama-French Factors

The model to be estimated is

$$dS_t = \alpha + \sum_{j=t-1}^{t} \beta_{j,MKT} MKT_j +$$

$$+ \sum_{j=t-1}^{t} \beta_{j,SMB} SMB_j + \sum_{j=t-1}^{t} \beta_{j,HML} HML_j + \varepsilon_t$$

where dS_t stands for the EMBI+ adjusted for Argentina spread in differences. The American Fama-French factors are the market excess return (MKT), the small minus big capitalization return (SMB) and the high minus low book to market value return (HML). I also include the factors lagged one period in the specification. The results are presented in Table 5.2.

First, for the EMBI+ aggregated index the contemporaneous MKT and SMB factors are very significant (more than 1% significance level), and so is the HML factor. All the coefficients are negative, implying that an increase in the American Fama-French factors cause a decrease in EM spreads. With respect to the lagged factors, only the MKT factor is significant. The adjusted R^2 is explaining almost half of the variance of the spread changes (43.6%). The market excess return appears to be the most relevant factor in order to explain EM spreads. This raises the question of why including the HML and SMB factors (CAPM). All econometric tests performed reject the possibility of HML and SMB to be jointly zero. That is, this factors are relevant to explain EM spreads, although not as the MKT factor. Moreover, these factors can help explaining how the US term premium and default premium affect EM sovereign spreads, things that would be not explained at all using only the market excess return alone.

Second, the exercise is repeated for the monthly EMBI+ series available per country. The EMBI+ for each country takes into account all sovereign bonds denominated in foreign currency, with an issuance (liquidity) higher than 500 US dollar million. The results are again striking. Coherently with respect to the result of the aggregated EMBI series, the regression show that for almost all countries, the Fama-French factors for the US market are highly significant. The exception of Argentina is explained by the time the country remained under default. The adjusted R^2 of the regressions are between 17 and 40% with the exception of Argentina, for which the R^2 is really low, which can be explained as before.

With respect to the negative coefficient signs, in the Fama and French series of papers, the actual return of stocks are usually related positively to the three factors (*MKT*, *HML*, *SMB*), with some exceptions generally related to extreme portfolios (see Fama and French, 1993). Thus, an increase in the Fama-French factors proxy for an increase in the *SDF* ($E_t(M_{t+1})$), which under the first order condition implies a decrease in expected excess returns ($E_t(R_{t+1})$)[13]. The negative signs of the American Fama-French shed light on how the term spread (correlated positively with the HML factor) and the default spread (correlated negatively with the SMB factor) affect EM sovereign spreads. In fact, the results show that an increase in the term spread on US corporations decreases EM spreads. The intuition here is that an increase in the premium paid by long term US corporate bonds decrease EM bond spreads, since EM bonds are generally long term bonds (at least the ones included for the EMBI index). With respect to the SMB factor, an increase in that factor correlates negatively with the default spread, that is, the premium for a given probability of default. When SMB decreases, the premium paid on a given default probability decreases, thus, EM and USC bond spreads decrease.

Since I work with EM spreads, a potential channel in which the

[13] Given a positive covariance between the *SDF* and the expected return.

American Fama-French factors may influence the spread is by the risk-free rate, usually the US government rate with a similar maturity to EM bonds. In Figure 5.4, I plot both the EMBI+ series and the US 10 year government yield. The higher proportion of the spread volatility comes from the EM yield not from the US rate. Moreover, in next subsection I will perform a Panel Error Correction Model and I control for the US Government rate. In Table 5.3, I include changes in the risk-free rate. ΔRf and ΔRf^2 stand for changes in the risk-free rate and for the same variable squared, in order to control for convexities in the relationship between the spread and the risk-free rate. These variables do not change the results commented before. Only for Morocco and Russia the changes in the risk-free rate present a significant effect, but without effecting the significance of the variables of interest.

5.2.2 EM Spreads and American Fama-French Factors: Long and Short-Run Relationship

In this subsection I follow Gonzalez and Levy (2006). They set a reduced long-run relationship between the EM spreads, the High Yield spread, the US government rate and the sovereign rating of the emerging country. They control for contagion for the Mexican and Russian crises with dummy variables. Since there is evidence of cointegration, according to the Granger Representation Theorem, the variables in the long-run equilibrium relationship have a panel error correction representation (PECM). This representation expresses the model in levels and differences in order to separate out the long-run and short-run effects. They use the Engle-Granger methodology (Engle and Granger, 1987) to estimate the PECM [14]. I follow their strat-

[14]This methodology is a two-stage modeling strategy. In stage one, the estimation of the long-run parameters of the cointegration equation is performed using a

egy, but instead of using the HY rate in the cointegration equation, I test the 10 year US government rate (a proxy for international liquidity), the VIX index (a measure of the volatility implied in the pricing of options on US stocks) and the American Fama-French factors (MKT, SMB and HML factors). The point here is that the American Fama-French factors also explain the High Yield spread, so we need to take one more step in direction of primitives, that is, preferences and expectations captured by the Fama-French factors as proxies of the stochastic discount factor. The inclusion of the VIX attempts to show that the effects of the Fama-French factors remain significant after controlling for volatility.

Following Gonzalez and Levy (2006), I estimate this model using the LSDV approach[15], so the effect of the country rating should be incorporated in the fix effect[16]. The first step regression is

$$ln(EMBI)_{it} = \alpha_{0i} + \alpha_1 ln(USGT10yr)_t + \alpha_2 ln(VIX)_t + \\ + \alpha_3 ln(MKT)_t + \alpha_4 ln(SMB)_t + \alpha_5 ln(HML)_t + \varepsilon_{it}$$

while the second step regression is

$$\Delta ln(EMBI)_{it} = \gamma_{0i} + \gamma_1 \check{z}_{t-1} + \sum_{j=0}^{q} \Gamma_{0j} ln(USGT10yr)_{t-j} + \sum_{j=0}^{p} \Gamma_{1j} ln(VIX)_{t-j} + \\ + \sum_{j=0}^{r} \Gamma_{2j} ln(MKT)_{t-j} + \sum_{j=0}^{q} \Gamma_{3j} ln(SMB)_{t-j} + \sum_{j=0}^{v} \Gamma_{4j} ln(HML)_{t-j} + \xi_{it}$$

where $\check{z}_{t-1}$ is the error coming from the first step regression lagged one period.

Before reporting the results, it is worth to discuss the main assumptions backing this specification. First, I assume that the marginal investor in US GT bond market is not the same as in EM sovereign

least squares dummy variable (LSDV) procedure. Stage two uses the error correction term lagged once and estimates a PECM to get the short-run dynamics.

[15] As in their case, I'm assuming that the time dimension is large and the estimation bias goes to zero.

[16] I'm assuming that the country credibility as a borrower and thus the rating is relatively stable over the period.

debt market. In other words, EM shocks do not affect US GT rates, contrary to flight to quality story in Felices et al. (2009). Second, there is not significant relation between the US GT 10 years rate and the American Fama-French.

The results for the PECM specifications are presented in Table 5.4. Two different specifications are discussed. The first one (equation 1 in the table) specifies a long run relation of the EM spreads with the US government 10 years interest rate, and the American Fama-French factors. The coefficient for the US GT10 rate goes in line with the literature, that is higher than one with positive sign, implying that an increase in the US rate is amplified for the EM spreads. The sign of the American Fama-French factors are negative, coherently with the previous section regressions. Note that the change in the market excess return causes a higher than proportional increase in the spread level, effect that is higher than for the US government rate. Thus, again the FF factor that is more relevant in order to explain in this case the long-run path of the EM spreads is the US market excess returns.

The short-run deviations from the path are captured in equations $1.b$ and $1.c$. In the first one I only include the change in factors lagged one period, while the second includes up to three lags. The relevant point is that the American Fama-French factors remain significant all the way. Their signs remain negative, while the main effect on the spread variation still comes from the excess return of the American market, specially in $t-1$. Note that the US GT rate coefficient is negative. This effect is found in the literature, implying that initially an increase in the US GT rate causes the EM spread to decrease, and after the shock the spread reacts and increases more than the increase in US GT rate (as is shown in the long-run equation)[17]. The problem with this specification is that we can not reject the existence of a

[17] See for example Uribe and Yue (2006)

unit root in the error series coming from the long-run relation (see Appendix IV, tests for $resid_1$).

In the second specification, I control for volatility in the US market, using the VIX index. Generally, an increase in volatility is associated with decreasing returns, so it should be related somehow to the US *SDF* and so to the American Fama-French factors. To avoid this, I work with the dimension of the VIX index that is orthogonal to the American Fama-French factors[18]. The long-run cointegration relation is in Equation $2.a$. Again, the EM spread relates positively with the USGT rate (but in this case less than proportionally), and with the VIX orthogonal to the Fama-French factors (in this specification the volatility seems to generate a more than proportional change in spreads). The Fama-French coefficients remain negative, as in previous regressions. The lags of the Fama-French factors remain significant up to 3 lags, with decreasing coefficients, while the HML factor seems to win importance in relation to the MKT excess return. The effect of the changes in USGT10 over the spread changes again is negative in the very short-run (ie: an increase in US GT rate decreases spreads), while from the second lag on is positive. The short-run effects of the volatility included in the VIX index that is not explained by the American Fama-French factors is positive and significant on the EM spreads (higher volatility changes imply higher spread changes).

The American Fama-French factors are then significant in order to explain both the level and the changes in the EM spreads, controlling for international liquidity with the interest rate that the US government pays and for the US market volatility with the VIX index. In Gonzalez and Levy (2006) they use a time dummy for both the Russian and Mexican crises. I'm not using any time effect in the exercise. Thus, in an indirect way, I am yielding evidence that the

[18]VIXort is the error series coming from regressing VIX on MKT, SMB and HML

American Fama-French factors are "controlling" for those periods, so they drive contagion. In Figure 5.5 it can be seen that every time a contagion crisis took place, the volatility of the MKT factor, the HML and SMB factors increase. What is more, there are more periods of high volatility of the American Fama-French factors but they did not cause major changes in EM spreads. Therefore, it is a necessary condition for the existence of an EM contagion event to observe high volatility in American Fama-French factors, but not a sufficient condition.

Kaminsky et al. (2003) argue that for a contagion case to happen, three things should be present: surprise announcements, an abrupt capital flow reversal, and a leveraged common creditor. My argument fits in this line. The US is a common creditor for Emerging Markets[19]; the changes in US agent expectations are by definition surprises (innovations); and finally the need to have high exposure to EMs in order to see a contagion case. Usually, this high exposure is revealed by a period of relevant capital flows (causing for example high stock returns in EMs). Thus, a possible way to understand the causality is that once US agent expectations on future discount rates (US stochastic discount factor) change, those markets with high exposure suffer first from this change in investment appetite. High exposure to capital inflows means, for example, high domestic liability dollarization (DLD) or high current account deficits (see Calvo 2005)[20]. Then these markets are prone to sudden stops, or current account crises (Russia 98, Brazil 2002). Contagion then starts from a shock to the US agent's expectations, that spreads to EMs, and if one market in particular falls, then the feedback potentiates the run from

[19]Although the US the biggest debtor in absolute terms, it is also a major lender by itself, or at least the biggest financial intermediary between other developed countries and EMs

[20]Note that I'm thinking in exposure from both sides: the investor of a developed market, and the EM country. The first might be overexposed to an EM country, and the second might be overexposed to changes in capital flows.

other markets (ie: due to microstructural issues like herding).

A crucial assumption rests behind these lines: the Fama-French factors in their job to proxy for the stochastic discount factor are exogenous to changes in EMs. Home bias is a proven fact (although declining in the last years), investors prefer domestic to international assets, and developed to non developed market assets. Thus, a shock in an EM market[21] should not have an impact on the US expected future discount rates. US stock prices and corporate bonds should not suffer that much. The assumption is that the initial shocks are US domestic. Moreover, this can explain why some EM crises remained local (Argentina 2001, Turkey 2002, Ecuador 1999, even the Asian crisis did not create a general increase in EM spreads) and did not spread as in other cases (Russia 1998 or Brazil 2002).

5.3 Principal Component Analysis

The literature has used principal components to study EM spreads (see Grandes (2007), Sløk and Kennedy (2004) and Fuentes and Godoy (2005)). In this section I take similar steps, and work with the first principal component[22].

5.3.1 Principal Component Analysis for EM and USC spreads

The literature has taken profit of the fact that emerging market spreads are highly correlated (see Appendix *I*), by finding the vector that explains the higher proportion of the common volatility. This vector is the first principal component, and this vector is understood as global risk aversion or global investment appetite factor (see McGuire and Schrijvers 2003; Sløk and Kennedy 2004).

In this paper I perform principal component analysis for two dif-

[21] A shock that has no clear incidence on relevant commodity prices.
[22] Appendix III presents the principal component analysis procedure.

ferent sample sets: *i*) a set that includes the US corporate spreads and the aggregated EMBI+ [23]. This sample includes five rankings of US corporate bonds: AAA, AA, A, BB, High Yield; plus the EMBI+ (adjusted for Argentina); *ii*) a set including monthly EMBI+ spreads for thirteen emerging markets. Results are presented in Table 5.5.

5.3.1.1 Sample I: US Corporate Spreads and EMBI+

With respect to the first sample, the one including the USC and the EMBI+, it is clear the relation between level factor and credit quality (the absolute value of the first component) decreases as the credit quality falls, meaning that an increase in the first component affects AAA bond spreads more than HY and EMBI+ [24]. Note that there is not a significant difference in the level factor between AAA, AA, A and BB ratings (Figure 5.5a).

5.3.1.2 Sample II: 13 Emerging Countries EMBI+ spread

For the second sample, the one including thirteen EMs, the level factor does not present the same clear reading as before in relation to credit ratings. However, Argentina, Ecuador, and Russia show lower absolute values than the rest of the sample. These countries defaulted during the sample period, so this goes in line to the observed fact in the previous case (Figure 5.5b). In both samples the importance of the first principal component is clear, as they explain 57 and 68% of the common volatility, respectively. Note that the loadings of this sample are not that different from the loadings of the US corporates and the aggregated EMBI+. This could be understood as proof that the first principal component explains more or less the same for the different countries/USC bonds[25].

[23]The aggregated index, corrected by the argentinean default

[24]As described in Singleton (2006), the first principal component of a set of bond spread time series represents a level factor.

[25] Note that in this exercise I have not controlled for the rating of each country (ie: investment grade or not). McGuire and Schrijvers (2003) show that the dif-

5.3.2 Global Risk Aversion and American Fama-French Factors

The relevance of Fama-French factors in explaining the proxy for global investment appetite is tested. That is, the first principal component studied in the previous section. I work with the first component coming from two samples: (i) the 13 EM sample; and (ii) the US corporate bond sample[26]. The model to test is then

$$PC^1(dS_t) = \alpha + \beta(1)MKT_t + \beta(2)SMB_t + \beta(3)HML_t + \varepsilon_t$$

where $PC^1(dS_t)$ stands for the first principal component coming from the correlation matrix of the debt spreads in differences (dS_t). The US Fama-French factors are the market excess return (MKT), the small minus big capitalization return (SMB) and the high minus low book to market value return (HML). In other specifications I include the momentum factor [27], the VIX index (the dimension of the index orthogonal to the American Fama-French factors), and the American Fama-French factors lagged one period. The results are in Tables 5.6 and 5.7.

5.3.2.1 Global Risk Aversion and American Fama-French Factors: US Corporate Bonds

For the US Corporate sample, the first principal component or level factor regressions also show that the Fama-French factors are significant, as seen in the seven regressions included in Table 5.6. The signs are positive for the Market, the SMB and HML factors. Since the loadings of the first factor are negative for all bond-ratings included in the sample (see Table 5.7), an increase in one of the fac-

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ferences in loadings of the first principal component are not significant between investment and non-investment countries.

[26]For the aim of this section, I find better to exclude the aggregated EMBI+ from this sample, and focus only in the US corporate bonds.

[27]see Carhart (1997).

tors causes a decrease in USC bond spreads.

In regression 2, the momentum factor appears to be significant with negative sign. In regression 3 the inclusion of the VIX index orthogonal to American Fama-French factors) shows no significance. Note that by construction, the $VIXo$ variable is of three orders higher than the other factors. However, when including the Fama-French factors lagged one period, the MKT factor looses significance. The implied volatility coming from option prices shows significance both for the actual period and the lagged one, although with different signs. The higher impact comes from the lagged one (with positive sign), so an increase in volatility has a combined effect of decreasing the spread on USC.

Finally, in regressions 6 and 7, changes in the risk-free rate as well as the risk-free rate squared are included, in order to control for convexities in the relationship between spreads and risk-free rate. The previous results are robust to the inclusion of the risk-free effect.

5.3.2.2 Global Investment Appetite and American Fama-French Factors: Emerging Market Sample

For the thirteen emerging country sample, the Fama-French factors are significant in the seven regressions I present in Table 5.8, except for the HML factor in regression 4. The signs are positive for all factors (except risk-free interest rate when included), but remember that the loading of the first factor is negative for all countries in the sample. That means that an increase in one of the factors causes a decrease in EM sovereign spread. This result is coherent with the results coming from the regressions on the previous section.

On the other side, the momentum factor shows no significance (regressions 2-7), although the inclusion of the lagged factors makes the lagged MOM factor to be significant with positive sign. The inclusion of the US market volatility implied in option prices ($VIXo$) is not significant in specification 3, but remains significant when the lagged factors are included. Note that by construction this variable is of 3 orders less than the other factors. Thus the impact of the implied volatility orthogonal to the Fama-French factors is much lower than the MKT, the SMB or the HML. What is more, as in the case of the USC bonds, the period t volatility appears with negative sign, while the lag term shows a positive one. Again, the positive coefficient dominates the negative one, implying that an increase in the US market volatility that is not controlled with the US Fama-French factors makes the EM spreads to decrease, a result that is not intuitive at all. In spite of the immediate positive reaction of EM spreads to an increase in volatility, the time-aggregated effect is a decrease in the EM spreads. In regressions 6 and 7, changes in the risk-free rate as well as the risk-free rate squared are included in order to control for convexities in the relationship between spreads and risk-free rate. The previous results are robust to the inclusion of the risk-free effect.

Finally, in Figure 5.6, I plot the volatility[28] of the first principal component for the EM sample and the volatility of the American Fama-French factors. In the previous section I presented the hypothesis that in order to observe contagion phenomena, the American Fama-French factors should experience an increase in volatility. Note that the reciprocal is not true (ie: not in every case in which the American Fama-French factor volatility increase the global investment appetite volatility increases, at least in a dramatic way as in 1998 and 2002). Thus, American Fama-French are a necessary condition for EM contagion to exist, but not a sufficient condition. This may help to understand why the Argentinean 2001 crisis did not spread contagion on other markets, nor the Brazilian or Turkish depreciations (1999 and 2001, respectively). If a previous contagion case had already made the agents to reallocate portfolios, a new shock would not surprise overexposed agents. This goes in line with Kaminsky et al.

[28] Rolling standard deviation for a 10 day window.

(2003) on their requirements of surprise and capital flow reversals for the existence of contagion.

Summing up, in this section I find that the American Fama-French factors are significant in order to explain both the first principal component for the emerging market spreads and the US corporate spreads. The positive sign of the factors, given that the loadings are negative, indicates that an increase in the factors generates a decrease in the spread, which is coherent to the previous results in Section 2. The higher absolute value of the coefficients for the EM sample indicates the higher incidence and volatility of the relation between the first principal component of the EM sample in relation to the USC sample.

5.4 American Fama-French Factors as proxy for Factor Innovations

Petkova(2006) shows that the Fama-French factors can be considered as proxys for innovations in variables that forecast future returns, in the spirit of Merton (1973) or Campbell and Viceira (1999) Intertemporal CAPM. The variables used as predictors of future returns are the aggregate dividend yield, the term spread, the default spread and the one-month Treasury-bill yield. The author finds that a model including the innovations of these state variables explains the cross-section of stock returns better than the Fama-French factors. What is more, she finds that the *HML* factor proxys for a term-spread surprise factor, while the *SMB* proxys for a default-spread surprise factor.

Following the author, but instead of using the Fama-French factors as proxys for the US stochastic discount factor, I use the market excess return, the aggregate dividend yield[29], a default spread (Aaa-

[29]The dividend yield series are from Schiller's web page. The variable is constructed as the sum of the last twelve months aggregated dividends over the aggregated market price. The results are for nominal variables, although no relevant

Baa bond yield), a term spread (10 year - 1 year spread), and the one-month T-bill[30]. The election of the variables has to do with both the yield curve and the conditional distribution of the investment opportunity set. For the yield curve, the short term interest rate T-bill is used (Fama and Schwert 1979), and the term spread (Campbell 1987) in order to capture the level and slope of the yield curve. The conditional distribution of asset returns is characterized by its mean and variance. The time series literature has identified variables that proxy for variations in mean and variance, which are the aggregate dividend yield (Campbell and Shiller 1988b), the default spread (Fama and French, 1989) and interest rates. Related to this, Merton (1973) states that stochastic interest rates are important factors of the change in investment opportunity sets. Therefore, the default spread, the dividend yield, and interest rate variables have been used as proxys for time-varying risk premia under changing investment opportunities.

5.4.1 Factor Innovation Estimation

I estimate a first-order VAR system following Campbell (1996). The first-order VAR specification is the following:

$$\begin{pmatrix} R_{M,t} \\ DIV_t \\ TERM_t \\ DEF_t \\ RF_t \\ R_{HML,t} \\ R_{SMB,t} \end{pmatrix} = A \begin{pmatrix} R_{M,t-1} \\ DIV_{t-1} \\ TERM_{t-1} \\ DEF_{t-1} \\ RF_{t-1} \\ R_{HML,t-1} \\ R_{SMB,t-1} \end{pmatrix} + u_t$$

where the first element of the vector is the market excess return ($R_{M,t}$); then the dividend yield (DIV_t); the term spread as defined before ($TERM_t$); the default spread (DEF_t), the risk-free rate (RF_t) and

changes are found if data in real terms is used.

[30]The data on Aaa and Baa bond yield, 10 year and 1 year US bond yields and one-month T-bill is from the FED

finally the FF factors ($R_{HML,t}, R_{SMB,t}$). The vector of innovations for each element in the state vector is u_t. The innovation coming from the dividend yield on the market excess return is orthogonalized, as well as the other variables. The orthogonalized innovation on each variable j is the component of the original j variable innovation orthogonal to the excess market return (ie, the orthogonalized innovation in DIV is the component of the original DIV innovation orthogonal to the excess market return). Therefore, it is the change in the dividend/price ratio with no change in the market return, interpreted as a shock to dividends. Similarly for the other factor innovations.

For the 1998-2006 time sample the results do not match the results of Petkova, in relation to a significant relation between the innovation to $TERM_t$ and the HML factor; and between the innovation to DEF_t and the SMB factor (see Table 5.9). I explain this difference mainly by the fact that I'm using the dividend yield ratio from Schiller (2002), which is not the same time series as in Petkova (2006). I then repeat the exercise for the 1963 to 2006 period, and then a significant relationship between the innovation to $TERM_t$ and the HML factor is found, but not between the innovation to DEF_t and the SMB factor (see Appendix V).

5.4.2 EM Spreads Using Factor Innovations

I use the innovations of the DIV, TERM, DEF and Rf factors instead of the Fama-French factors to check if the still can explain EM sovereign spreads. I use the innovations coming from the sample period 1998-2006. The regression is then:

$$dS_t = c_0 + c_1\hat{u}_t^{DIV} + c_2\hat{u}_t^{TERM} + c_3\hat{u}_t^{DEF} + c_4\hat{u}_t^{Rf} + \varepsilon_t$$

where dS_t stands for the EMBI+ spread in differences; the variables $\hat{u}_t^{DIV}$; $\hat{u}_t^{TERM}$; $\hat{u}_t^{DEF}$ and $\hat{u}_t^{Rf}$ stand for the dividend-yield ratio innovation, the term spread innovation, the default spread innovation, the risk free rate innovation (respectively), orthogonalized with respect to the market excess return. In Table 5.10, the results for the EMBI+ and for each country are reported. The market factor is highly significant for all the countries in the sample, while the innovations of the dividend yield, the term spread and the default spread are significant for some countries. The dividend yield innovation is significant for the aggregated index (EMBI+), Mexico, Peru, Bulgaria and Russia. The term spread innovation is significant for Nigeria and Poland. The default spread is only significant for Argentina; and the interest rate innovation is significant only for Venezuela. The short sample period might be the explanation for the loss of significance of the innovations. The adjusted R^2s vary according to the countries: for those that experienced defaults (Argentina and Ecuador) the value is very low, while for Mexico, Panama and Venezuela is very high (near 26%). The explicative power for the aggregated EMBI+ is around 20%.

In order to test robustness in relation to the time period used to calculate the innovations, I did the same exercise but for the period 1963-2006. The results do not change much (see Appendix V), although the adjusted R^2s are in general higher. The significance of the market factor is going to be key for the asset-pricing model tests in the next section.

5.5 EM Stock Markets and American Fama-French Factors

To conclude with emerging market assets and its relation with the US stochastic discount factor in this section I study the EM stock markets. The exercise is similar to the one done for EM sovereign debt spreads, the only difference is that the monthly stock excess return is the dependent variable in the regressions (excess return compared to US risk-free rate). Table 5.11 reports the results for nominal returns per country[31]. Only in the case of Egypt there is no relation between the stock market return and the American Fama-French factors. Note that Egypt is the only country of the sample that does not have ADRs[32], so the market is not expected to be integrated, thus the result is not an unexpected one. For all other countries in the sample, at least one of the factors is significant.

5.6 Formal Asset Pricing Model Tests

The aim of this section is to test the validity of an asset-pricing model specification for emerging country sovereign debt in which only external factors are taken into account. In Appendix *VII* the reader has a short theory review on these formal tests. Below I report the tests results.

5.6.1 Formal Asset Pricing Model Tests: Evidence

Table 5.12 presents the results of formal statistics to test the validity of an asset pricing model for emerging country sovereign debt returns, using: *a*) only the US Fama-French factors; *b*) the US Fama-French factors plus the US risk free interest rate. According to these tests, we can reject the model for the time series in the first case (GRS test). However, by including the risk-free interest rate we can not reject the constants to be jointly zero. However, the cross-sectional test show that the model is not correctly specified. That is, the alpha, or

[31] In Appendix *V* I present the results for real returns.

[32] A Depositary Receipt is a negotiable U.S. security that generally represents a company's publicly traded equity or debt. Depositary Receipts are created when a broker purchases the non-U.S. company's shares on the home stock market and delivers those to the depositary's local custodian bank, which then instructs the depositary bank, such as The Bank of New York, to issue Depositary Receipts. In addition, Depositary Receipts may also be purchased in the U.S. secondary trading market. Depositary Receipts may trade freely, just like any other security, either on an exchange or in the over-the-counter market and can be used to raise capital.

the Jensen's constant, can be rejected to be jointly zero.

The result of the GRS for the model including the risk-free interest rate is extremely interesting. We can not reject the asset pricing model in which only external factors determine EM sovereign debt returns. The rejection of the cross-sectional tests comes not as a surprise. Note that the sample is very heterogenous (ie: includes countries under default).

With respect to EM stock returns, for a sample available for EMs in the IMF IFS database, the results for the time series GRS statistic is again the rejection of the model at any relevant significance level. I work with different sub-samples, and the result is robust. To sump up, the model specification that can not be rejected as a good asset-pricing for EM sovereign debt is rejected for EM stock markets.

In spite of these formal asset pricing tests problems (see Lewellen et al. 2010), the idea that EM sovereign returns can be explained only by external factors remains seductive, and can be associated with the high integration of financial markets. Therefore, EM sovereign debt markets seem to be more integrated than the stock markets. In fact, some facts point at this conclusion. First of all, sovereign debt included in the EMBI+ has high liquidity (to be included in EMBI+ each issuance should be bigger than 500 US million dollars); the issuances are in a common currency (mostly in US Dollars; other in Euros or Yens); they are issued in foreign developed markets (New York or London), that is, domestic laws do not apply for this kind of sovereign debt, which reduce the degrees of freedom of the potential defaulters. All these clauses make these sovereign debt markets to be highly integrated to core financial systems. On the contrary, stock markets might not present the same degree of integration (see Carrieri and Majerbi 2006), who find that while local risk is still a relevant factor for time-variation of EM's returns, none of the countries appear to be completely segmented).

5.7 Conclusions

The main contribution of this paper is to show that the US stochastic discount factor is behind the co-movement increase of EM sovereign debt spreads and of US corporate spreads. I proxy for the US stochastic discount factor using the American Fama-French factors.

I find that the American Fama-French factors are significant in order to explain EM sovereign debt spreads (EMBI+). What is more, I follow Gonzalez and Levy (2006)in setting a Panel Error Correction Model, in order to disentangle the long and short-run relationship between the EM spreads and the American Fama-French factors, controlling both for the US government rate and the US market volatility. The Fama-French factors remain significant in order to explain both short and long run relationships.

Taking profit from the high correlation of EMBI+ series among EM countries, I prove that the Fama-French factors are also significant in explaining their first principal component (a proxy for Global Investment Appetite). Moreover, I show that in order for contagion to exist, there must be an increase in volatility of the MKT, SMB and HML factors. Not every time such increase in volatility takes place there is an associated contagion event in EMs. Thus, I state that high volatility in American Fama-French factors is a necessary but not sufficient condition for EM contagion to exist.

I extend the analysis to EM stock markets, and show that the Fama-French factors remain significant, which can also be associated to contagion in stock markets. Finally, I present formal tests for asset-pricing models using only the external factors in order to explain EM sovereign spreads and stock returns. The results are inconclusive and more research should be done on this, although the importance of the American Fama-French factors becomes clear as we can not reject the correct asset model specification in the GRS test, including the risk-free interest rate as a fourth factor.

More research should also be done on the assumption that the American Fama-French factors are exogenous to EM shocks, and also on how expectations of future payoffs can be changed due to shocks to innovations on the expected future discount rates. Also, it is important to understand why in some cases the volatility in the American Fama-French factors ignite a period of EM financial turmoil, while others do not have the same effect.

Table 5.1: Two Periods of EM Financial Distress: 1998 & 2002

Notes: USC and EM Bonds, Spread in bps. EMBI+ * = EMBI+ Spread Adjusted for Argentina

1998 Financial Distress Period				2002 Financial Distress Period			
	June 1998	Sept 1998	Sept - June 1998 var %		April 2002	Oct 2002	Oct - April 2002 var %
BBB	127	200	56.8%	AA	19	47	153.2%
HY	366	573	56.5%	AAA	35	78	124.0%
A	95	145	52.3%	BBB	214	333	55.3%
AA	80	121	52.0%	A	88	137	54.8%
AAA	77	110	43.4%	HY	665	1012	52.1%
EMBI+ *	609	1522	149.8%	EMBI+ *	502	831	65.7%
Russia	866	4986	476.0%	Brazil	757	2022	167.0%
Venezuela	577	2129	268.9%	Nigeria	1155	2924	153.2%
Nigeria	944	2362	150.2%	Ecuador	996	1992	99.9%
Ecuador	813	1985	144.1%	Peru	444	809	82.2%
Morocco	444	1064	139.6%	Colombia	572	952	66.4%
Philippines	401	953	137.7%	Mexico	242	384	58.9%
Bulgaria	611	1365	123.5%	Poland	171	262	53.4%
Brazil	620	1377	122.0%	Morocco	365	544	49.2%
Argentina	489	1085	121.9%	Panama	358	495	38.2%
Mexico	456	952	108.6%	Indonesia	292	397	36.1%
Thailand	363	717	97.7%	Thailand	91	123	35.0%
Peru	493	937	90.1%	Philippines	377	504	33.7%
Korea	454	792	74.5%	Argentina	4830	6398	32.5%
Poland	202	338	67.1%	Venezuela	885	1082	22.3%
Panama	362	602	66.2%	Malaysia	156	188	20.3%
Colombia	na	na	na	Russia	479	546	14.0%
Malaysia	na	na	na	Bulgaria	389	346	-10.9%
Indonesia	na	na	na	Korea	88	74	-15.7%

Table 5.2: Data Sample

	US Corporate Bonds						Emerging Markets Sovereign Bonds												
	AAA	AA	A	BBB	HY	EMBI	Arg	Bra	Mex	Peru	Ven	Ecu	Pan	Bul	Mor	Nig	Pol	Rus	Thai
Mean	56.2	50.7	93.7	172.3	559.7	660.6	2790.4	810.5	348.1	490.0	842.6	1490.6	393.0	470.4	399.5	1327.1	169.9	1228.2	156.2
STD	41.5	63.4	52.9	59.9	186.8	327.2	2395.3	375.2	180.2	183.4	332.9	936.0	84.2	309.9	207.1	655.2	87.4	1521.8	119.8
Max	135.4	158.6	198.8	332.7	1012.1	1521.7	6836.0	2022.0	952.0	937.3	2129.2	4415.8	602.2	1365.2	1064.5	3430.1	337.8	5938.5	716.7
Min	-19.7	-69.6	-8.9	65.4	315.6	192.3	374.0	238.3	110.7	141.3	241.1	567.7	194.3	68.6	75.0	451.6	39.6	106.0	41.9
Kurtosis	-0.682	-0.719	-0.490	-0.633	-0.973	-0.130	-1.713	1.532	1.278	-0.686	1.166	1.814	-0.303	-0.899	-0.095	0.307	-1.400	2.327	7.171
Skewness	-0.033	-0.336	-0.284	0.150	0.472	0.785	0.346	1.202	1.192	-0.103	0.625	1.593	-0.072	0.312	0.446	0.814	-0.239	1.843	2.359

Correlations

	AAA	AA	A	BBB	HY	EMBI+	Arg	Bra	Mex	Per	Ven	Ecu	Pan	Bul	Mor	Nig	Pol	Rus	Thai
AAA	1																		
AA	0.96	1																	
A	0.91	0.95	1																
BBB	0.60	0.60	0.80	1															
High Yield	0.20	0.21	0.48	0.87	1														
EMBI+	0.55	0.56	0.60	0.52	0.36	1													
Argentina	-0.70	-0.79	-0.66	-0.16	0.11	-0.43	1												
Brazil	0.14	0.09	0.28	0.67	0.73	0.63	0.22	1											
Mexico	0.55	0.56	0.57	0.43	0.24	0.95	-0.47	0.55	1										
Peru	0.43	0.42	0.58	0.74	0.73	0.78	-0.17	0.80	0.74	1									
Venezuela	0.20	0.16	0.31	0.54	0.59	0.76	0.03	0.76	0.72	0.78	1								
Ecuador	0.54	0.50	0.53	0.46	0.27	0.64	-0.34	0.35	0.49	0.45	0.42	1							
Panama	0.42	0.39	0.54	0.67	0.63	0.83	-0.11	0.76	0.78	0.93	0.81	0.57	1						
Bulgaria	0.67	0.72	0.74	0.53	0.35	0.88	-0.64	0.40	0.89	0.78	0.62	0.56	0.77	1					
Morocco	0.56	0.59	0.67	0.62	0.48	0.94	-0.41	0.65	0.94	0.86	0.79	0.50	0.86	0.92	1				
Nigeria	0.49	0.45	0.64	0.87	0.82	0.56	-0.06	0.76	0.46	0.81	0.63	0.60	0.77	0.55	0.63	1			
Poland	0.67	0.69	0.78	0.74	0.57	0.85	-0.45	0.64	0.83	0.85	0.68	0.64	0.83	0.89	0.91	0.77	1		
Russia	0.50	0.51	0.47	0.26	0.06	0.91	-0.49	0.39	0.90	0.52	0.60	0.48	0.59	0.75	0.79	0.25	0.64	1	
Thailand	0.47	0.48	0.43	0.20	0.05	0.67	-0.48	0.28	0.82	0.56	0.56	0.22	0.53	0.76	0.75	0.26	0.66	0.64	1

Table 5.3: EM Sovereign Spreads and Fama French Factors

Notes: $dS_{i,t}$ stands for the country i sovereign debt spread in differences. The US Fama French factors are the market excess return (MKT), the small minus big capitalization return (SMB) and the high minus low book to market value return (HML). (-1) stands for the one-period lag variable. ΔRf and ΔRf^2 stand for changes in the risk-free rate and for the same variable squared, in order to control for convexities in the relationship between the spread and the risk-free rate. The series are from French's webpage. Newey-West standard errors in parenthesis, 5 lags. Significance levels reported: * 10%, ** 5%, *** 1%. The R^2s from each regression are reported in percentage form.

	EMBI+	Argentina	Brazil	Mexico	Peru	Venezuela	Ecuador	Panama	Bulgaria	Morocco	Nigeria	Poland	Russia
MKT	-0.010***	-0.009	-0.013***	-0.010***	-0.008***	-0.0139***	-0.013***	-0.008***	-0.009**	-0.011***	-0.013***	-0.011***	-0.009**
SMB	-0.005***	-0.001	-0.006***	-0.004**	-0.006***	-0.005*	-0.002	-0.004**	-0.005**	-0.008**	-0.001	-0.003	-0.007*
HML	-0.005**	0.002	-0.007**	-0.002	-0.004	-0.007**	-0.012**	-0.001	-0.0004	-0.006	-0.002	-0.005*	-0.006
MKT(-1)	-0.008***	-.0107**	-0.008**	-0.006*	-0.007**	-0.007*	-0.014***	-0.004**	-0.008**	-0.006	-0.011**	-0.009***	-0.011*
SMB(-1)	-0.003	-0.007	-0.001	-0.004	-0.002	-0.004	-0.004	-0.003	-0.006**	-0.004	-0.006*	-0.002	-0.007
HML(-1)	-0.004	-0.009	-0.001	-0.0002	-0.001	-0.003	-0.008**	-0.002	-0.006*	-0.002	-0.007*	-0.005	-0.009
Cons	0.003	0.012	0.006	-0.0034	-0.00008	0.009	0.018	0.003	-0.008	-0.002	0.011	-0.0007	0.0002
$adjR^2$	43.60	1.48	34.11	39.17	21.94	30.04	30.47	35.17	28.64	18.65	24.83	17.61	23.95
N	96	96	96	96	96	96	96	96	96	96	96	96	96

Table 5.4: EM Sovereign Spreads and Fama French Factors

Notes: $dS_{i,t}$ stands for the country i sovereign debt spread in differences. The US Fama French factors are the market excess return (MKT), the small minus big capitalization return (SMB) and the high minus low book to market value return (HML). (-1) stands for the one-period lag variable. ΔRf and ΔRf^2 stand for changes in the risk-free rate and for the same variable squared, in order to control for convexities in the relationship between the spread and the risk-free rate. The series are from French's webpage. Newey-West standard errors in parenthesis, 5 lags. Significance levels reported: * 10%, ** 5%, *** 1%. The R^2s from each regression are reported in percentage form.

	EMBI+	Argentina	Brazil	Mexico	Peru	Venezuela	Ecuador	Panama	Bulgaria	Morocco	Nigeria	Poland	Russia
MKT	-0.010***	-0.009	-0.014***	-0.010***	-0.008***	-0.014***	-0.013***	-0.008***	-0.008**	-0.011***	-0.013***	-0.011***	-0.009**
SMB	-0.005***	-0.001	-0.005**	-0.003	-0.006**	-0.005	-0.000	-0.004**	-0.005*	-0.007*	0.001	-0.003	-0.008**
HML	-0.005**	0.003	-0.008**	-0.002	-0.004	-0.007**	-0.012**	-0.001	-0.000	-0.006	-0.003	-0.006*	-0.004
Δ Rf	0.004	0.002	0.008	0.008	0.002	-0.007	0.003	0.001	-0.001	0.012	0.001	-0.006	0.014
ΔRf^2	-0.001	0.002	0.000	-0.000	-0.001	0.001	-0.000	-0.001	0.000	0.000	0.001	0.001	-0.003
MKT(-1)	-0.008***	-0.010*	-0.008**	-0.005	-0.007*	-0.009*	-0.015***	-0.004*	-0.008*	-0.005	-0.012**	-0.011**	-0.008
SMB(-1)	-0.004	-0.010	-0.000	-0.004	-0.001	-0.003	-0.002	-0.003	-0.006**	-0.005	-0.005	-0.000	-0.010*
HML(-1)	-0.003	-0.011	0.001	0.001	-0.001	-0.005	-0.007*	-0.002	-0.006*	0.001	-0.008	-0.006	-0.005
Δ Rf(-1)	0.005	-0.023	0.009	0.006	0.012	-0.004	0.008	-0.000	-0.002	0.013*	-0.002	0.005	0.009
ΔRf^2(-1)	-0.001	-0.002	0.000	0.000	0.002	0.000	0.002	0.000	-0.000	-0.000	0.001	-0.001	-0.004**
Cons	0.011	0.014	0.000	-0.007	-0.004	0.004	0.008	0.004	-0.007	-0.006	-0.002	-0.003	0.020
$ADJ\,R^2$	45.1	1.0	32.3	38.7	20.4	28.1	28.9	32.0	24.1	17.4	23.3	15.8	31.9
N	93	93	93	93	93	93	93	93	93	93	93	93	93

Table 5.5: Panel Error Correction Model

Variable	1.a		1.b		1.c		2.a		2.b	
LNMKT	-1.745	***					-2.321	***		
LNSMB	-0.939	***					-1.231	***		
LNHML	-2.668	***					-3.502	***		
LNUSGT10	1.055	***					0.591	***		
LNVIXort							1.383	***		
RESID(-1)			-0.026	***	-0.013	***			0.024	***
DLNUSGT10			-0.255	***	-0.241	***			-0.065	
DLNMKT			-0.360	***	-0.694	***			-1.08	**
DLNSMB			-0.206	***	-0.236	***			-0.571	***
DLNHML			-0.317	***	-0.257	***			-1.091	***
DLNVIXort									0.353	***
DLNMKT(-1)					-1.094	***			-0.679	***
DLNSMB(-1)					-0.516	***			-0.301	***
DLNHML(-1)					-0.724	***			-0.397	***
DLNUSGT10(-1)									0.105	*
DLNVIXort(-1)									-0.047	*
DLNMKT(-2)					-0.475	***			-0.518	**
DLNSMB(-2)					-0.470	***			-0.415	***
DLNHML(-2)					-0.618	***			-0.664	***
DLNUSGT10(-2)									-0.191	
DLNVIXort(-2)									0.104	***
DLNMKT(-3)					-0.132	**			-0.218	**
DLNSMB(-3)					-0.188	***			-0.13	**
DLNHML(-3)					-0.247	***			-0.315	***
DLNUSGT10(-3)									0.109	**
DLNVIXort(-3)									0.11	***
DLNEMBI(-1)			0.340	***	0.246	***			0.249	***
DLNEMBI(-2)			-0.106	***	-0.010				-0.066	**
C	-0.153		-0.008	***	-0.009	***	0.573	***	-0.006	***
Adjusted R-squared	0.5871		0.1475		0.2852		0.8342		0.3836	
Total panel observations:	1724		1674		1656		1724		1656	

Table 5.6: Principal Component Analysis Results

a) EMBI+ spreads sample: 1998-2006

PC	Explained Variance	Country	PC 1 Loadings
1	56.9	Arg	-0.06573
2	8.1	Bra	-0.30024
3	7.7	Mex	-0.34169
4	6.0	Per	-0.30551
5	5.8	Ven	-0.28089
6	4.3	Ecu	-0.18021
7	2.6	Pan	-0.31634
8	2.2	Bul	-0.31402
9	1.8	Mor	-0.32685
10	1.6	Nig	-0.28212
11	1.2	Pol	-0.27998
12	1.0	Rus	-0.21957
13	0.7	Tha	-0.26901

b) USC and EMBI+ spread sample: 1998-2006

PC	Explained Variance	Category	PC 1 Loadings
1	68.4	AAA	-0.44591
2	18.2	AA	-0.44196
3	7.8	A	-0.47303
4	2.8	BB	-0.4553
5	1.8	HY	-0.35109
6	1.0	EMBI+	-0.22696

Table 5.7: US Corporate Bond First Principal Component and Fama French Factors

Notes: $PC^1(dS_t)$ stands for the first principal component coming from the correlation matrix of the debt spreads in differences (dS_t). The US Fama French factors are the market excess return (MKT), the small minus big capitalization return (SMB) and the high minus low book to market value return (HML). MOM stands for the momentum factor, the series are from French's webpage. VIXo stands for the dimension of the VIX index orthogonal to the American Fama French factors. ΔRf and ΔRf^2 stand for changes in the risk-free rate and for the same variable squared, in order to control for convexities in the relationship between the spread and the risk-free rate. (-1) stands for the factor lagged one period. Newey-West standard errors in parenthesis, 5 lags. Significance levels reported: * 10%, ** 5%, *** 1%. The adjusted R^2s from each regression are reported in percentage form.

	1	2	3	4	5	6	7
MKT	2.163***	1.436*	1.437*	0.770	1.381	1.622	1.623
SMB	3.244***	3.721***	3.722***	2.961***	3.449***	2.860***	2.844***
HML	3.324**	3.007**	3.009**	1.615	3.726**	3.929**	3.816**
MOM		-1.399**	-1.402**	-1.324**	-1.134**	-1.140**	-1.097*
VIXo			-0.424		-80.810**	-82.289**	-79.120**
MKT(-1)				2.286**	0.200	-0.142	-0.060
SMB(-1)				0.391	-0.740	-0.671	-0.587
HML(-1)				-0.672	-2.919**	-3.401**	-3.429**
MOM(-1)				-0.581	-0.213	-0.183	-0.202
VIXo(-1)					93.919***	102.133***	98.280***
Δr						-3.440	-3.533
Δr^2						-1.177***	-1.211***
Δr(-1)							-0.623
Δr^2(-1)							0.296
Cons	-3.979	-2.519	-2.501	-1.340	-2.131	2.285	1.477
Adj. R^2	0.124	0.158	0.149	0.256	0.303	0.329	0.317
N	97	97	97	96	96	94	93

Table 5.8: 13 EM Bond First Principal Component and Fama French Factors

Notes: $PC^1(dS_t)$ stands for the first principal component coming from the correlation matrix of the debt spreads in differences (dS_t). The US Fama French factors are the market excess return (MKT), the small minus big capitalization return (SMB) and the high minus low book to market value return (HML). MOM stands for the momentum factor, the series are from French's webpage. VIXo stands for the dimension of the VIX index orthogonal to the American Fama French factors. ΔRf and ΔRf^2 stand for changes in the risk-free rate and for the same variable squared, in order to control for convexities in the relationship between the spread and the risk-free rate. (-1) stands for the factor lagged one period. Newey-West standard errors in parenthesis, 5 lags. Significance levels reported: * 10%, ** 5%, *** 1%. The adjusted R^2s from each regression are reported in percentage form.

	1	2	3	4	5	6	7
MKT	34.197***	32.917***	33.105***	28.036***	35.547***	36.320***	36.502***
SMB	13.888**	14.728**	15.002**	7.460*	14.075**	13.048**	12.705*
HML	25.008***	24.449***	24.920**	11.483	37.962***	38.196***	40.083***
MOM		-2.464	-3.129	-0.246	1.333	0.809	0.711
VIXo			-116.323		-1056.709**	-1063.543**	-1108.239**
MKT(-1)				31.712**	4.367	1.587	0.610
SMB(-1)				9.743	-4.438	-2.858	-4.404
HML(-1)				11.569	-17.482*	-20.394*	-21.249*
MOM(-1)				3.054	7.009**	7.726**	8.002***
VIXo(-1)					1133.650**	1150.405**	1205.825**
Δr						-20.704	-20.554
Δr^2						-1.712	-1.498
Δr(-1)							0.131
Δr^2(-1)							-2.337
Cons	-17.908	-15.337	-10.145	-30.403	-34.320	-24.841	-15.397
Adj. R^2	21.4	20.8	21.2	38.3	48.9	49.8	49.1
N	97	97	97	96	96	94	93

Table 5.9: Orthogonalized innovations on MKT and Fama French factors Sample 1998-2006

Notes: The variables $\hat{u}_t^{DIV}$; $\hat{u}_t^{TERM}$; $\hat{u}_t^{DEF}$ and $\hat{u}_t^{Rf}$ stand for the dividend-yield ratio innovation, the term spread innovation, the default spread innovation, the risk free rate innovation (respectively), ortoghonalized with respect to the market excess return. $\hat{u}_t^{HML}$ and $\hat{u}_t^{SMB}$ stand for the Fama French factor innovations, ortoghonalized with respect to the market excess return. The US Fama French factors are the market excess return (MKT), the small minus big capitalization return (SMB) and the high minus low book to market value return (HML). The series are from French's webpage. The t-statistics are inside parenthesis, and corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags. Significance levels reported: * 10%, ** 5%, *** 1%. The adjusted R^2s from each regression are reported in percentage form. The sample period is from February 1998 to December 2006.

Regression: $\hat{u}_t = C + c_1 MKT_t + c_2 SMB_t + c_3 HML_t + \varepsilon_t$

	$\hat{u}_t^{DIV}$	$\hat{u}_t^{TERM}$	$\hat{u}_t^{DEF}$	$\hat{u}_t^{Rf}$	$\hat{u}_t^{SMB}$	$\hat{u}_t^{HML}$
MKT	0.00527	-0.01234	-0.00231	0.00365	-0.34269***	0.62285***
SMB	0.00380	-0.00782	-0.02368	-0.00723	0.90866***	-0.09902***
HML	0.00925*	-0.02112	-0.01467	0.00165	-0.04388	0.82813***
C	4.47e-08	-9.80e-08	-1.41e-07	-2.39e-08	3.50e-06	2.23e-06
Adj. R^2	1.13	0.91	0.31	2.05	93.70	85.90
N	108	108	108	108	108	108

Table 5.10: EM Spreads using innovations on factors (1998-2006 sample)

Notes: dS_t stands for the EMBI+ spread in differences; the variables $\hat{u}_t^{DIV}$; $\hat{u}_t^{TERM}$; $\hat{u}_t^{DEF}$ and $\hat{u}_t^{Rf}$ stand for the dividend-yield ratio innovation, the term spread innovation, the default spread innovation, the risk free rate innovation (respectively), ortoghonalized with respect to the market excess return. The t-statistics are inside parenthesis, and corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags. Significance levels reported: * 10%, ** 5%, *** 1%. The adjusted R^2s from each regression are reported in percentage form. The sample period is from February 1963 to December 2006.

$$dS_t = c_0 + c_1 MKT + c_2\hat{u}_t^{DIV} + c_3\hat{u}_t^{TERM} + c_4\hat{u}_t^{DEF} + c_5\hat{u}_t^{Rf} + \varepsilon_t$$

	Embi+	Argentina	Brazil	Mexico	Peru	Venezuela	Ecuador	Panama	Bulgaria	Morocco	Nigeria	Poland	Russia
MKT	-0.00898***	-0.01017**	-0.01187***	-0.01063***	-0.00857***	-0.01224***	-0.00781**	-0.00869***	-0.00971***	-0.01045***	-0.01166***	-0.00959***	-0.00861**
$\hat{u}_t^{DIV}$	-0.023203*	0.01852	-0.02102	-0.02442*	-0.02689*	0.01415	-0.00689	-0.01311	-0.01896*	-0.00944	-0.01998	-0.02209	-0.05300**
$\hat{u}_t^{TERM}$	0.031172	0.16978	0.06654	0.02350	0.02834	0.06049	0.08029	-0.00185	0.034512	0.09338	-0.16116***	-0.11006*	0.0413125
$\hat{u}_t^{DEF}$	-0.03550	0.42009**	0.09570	-0.03473	0.02815	0.09391	0.07582	-0.05423	0.00058	0.00453	-0.03694	0.006972	-0.06418
$\hat{u}_t^{Rf}$	0.37819	2.22157	0.25499	-0.04052	0.08099	1.39234**	0.10097	0.30264	0.71415	0.28964	0.98682	0.52544	0.26191
C	-0.00752	0.00316	-0.00499	-0.01008	-0.00926	-0.00153	-0.00052	-0.00205	-0.01794	-0.01417	0.00206	-0.01012	-0.01642
Adj. R^2	20.98	7.35	19.46	26.02	10.03	25.39	2.21	26.42	17.40	9.02	19.52	11.34	10.19
N	97	97	97	97	97	97	97	97	97	97	97	97	97

Table 5.11: Emerging Stock Market Nominal Returns and American Fama French Factors

Notes: The t-statistics are inside parenthesis, and corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags. Significance levels reported: * 10%, ** 5%, *** 1%. The adjusted R^2s from each regression are reported in percentage form. The sample period is from February 1963 to December 2006.

Regression: $R_t = c_0 + c_1 MKT_t + c_2 SMB_t + c_3 HML_t + \varepsilon_t$

	Brazil	Mexico	Chile	Colombia	Peru	Indonesia	Philippines	Thailand
MKT	0.1745***	0.1164***	0.0431***	0.1694***	0.1137***	0.1463***	4.0420	0.1669**
SMB	0.0090	0.0534*	0.0487***	0.1248***	0.0335	0.0835	6.6043	0.0186
HML	-0.0847	-0.0515*	0.0478**	0.1998***	0.0548	0.0897	8.1233	0.0501
C	0.8538***	0.5298***	0.1672***	0.7236***	0.5837***	0.6883***	14.7678	0.6087**
Adj.R^2	47.89	54.15	14.88	12.20	14.51	19.99	3.06	12.19
N	108	108	107	108	108	108	107	107

	Malaysia	Korea	India	Pakistan	China	Egypt	Saudi Arabia	South Africa
MKT	0.0866	0.1160***	0.0375*	0.0467	0.1232***	0.0184	0.0217	0.0606***
SMB	0.0789*	0.0487	0.0645***	0.0966***	0.0359	-0.0021	0.0630**	0.0436***
HML	0.0578	-0.0083	0.0373	0.0487	0.0283	-0.0048	0.0399	0.0418**
C	0.1426	0.1859	0.1183	0.0606	0.3610	-0.0002	0.0307	0.2022
Adj.R^2	14.26	18.59	11.83	6.06	36.10	0.22	3.07	20.22
N	106	106	106	106	106	106	106	106

Table 5.12: Asset Pricing Models, a Formal Approach Test for EM spreads in differences as dependent variable

	MKT, HML, SMB	*MKT, HML, SMB, Rf*
GRS	12.485	0.761
Degrees of Freedom	13,80	13,79
Test Model	Reject	Do not reject
Cross-Sectional		11.0737
Degrees of Freedom		8,89
Test Model		Reject

Figure 5.1: Emerging Market Sovereign Debt Spreads, 1998-2006 (bps)

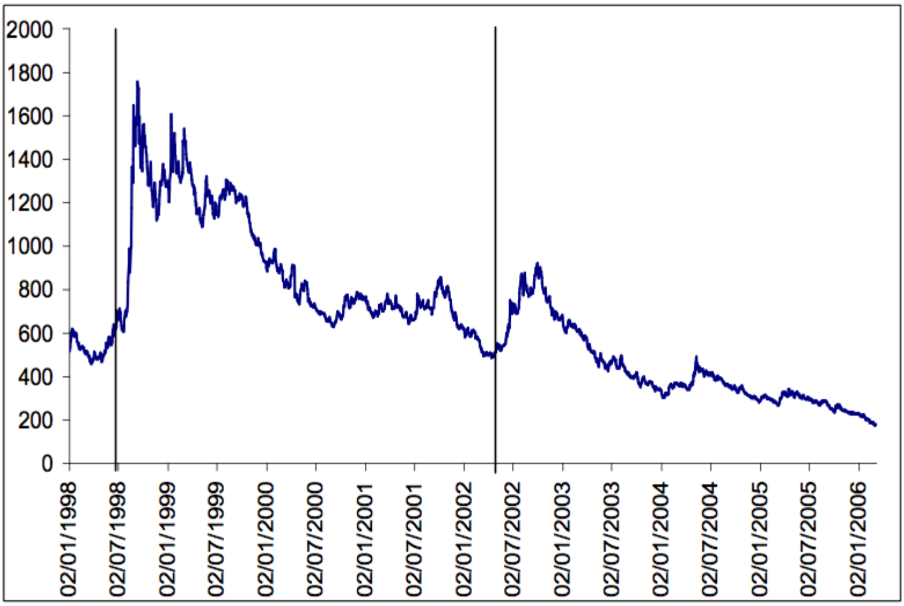


Figure 5.2: 2002 Emerging Market Financial Distress. EMBI+ Spread and USC Bond Spreads

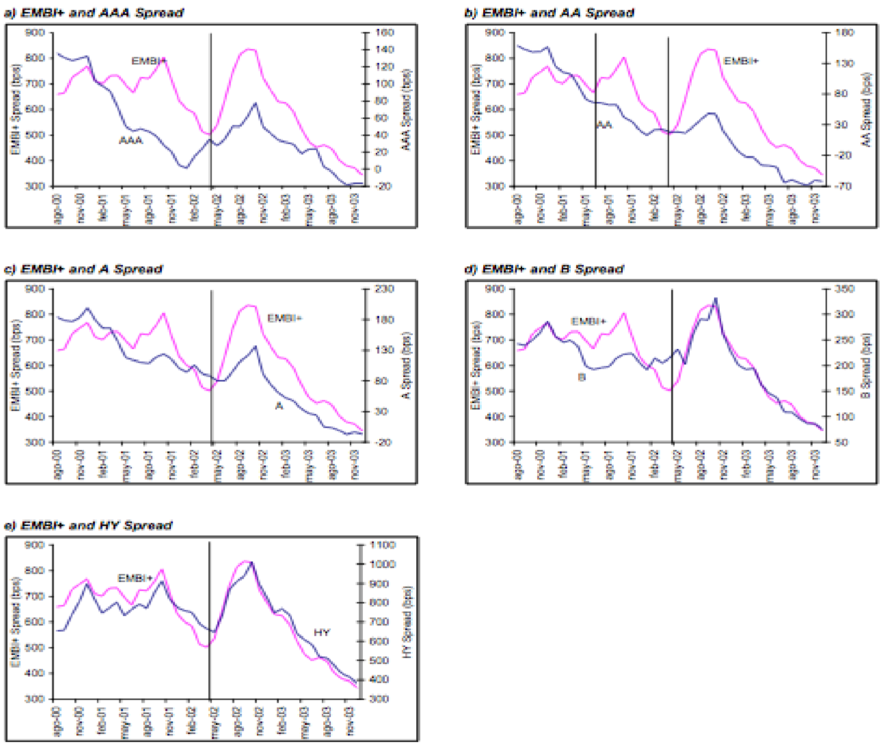


Figure 5.3: 1998 Russian Crisis. EMBI+ Spread and USC Bond Spreads

Figure 5.4: EMBI+ and US GT 10 years rate

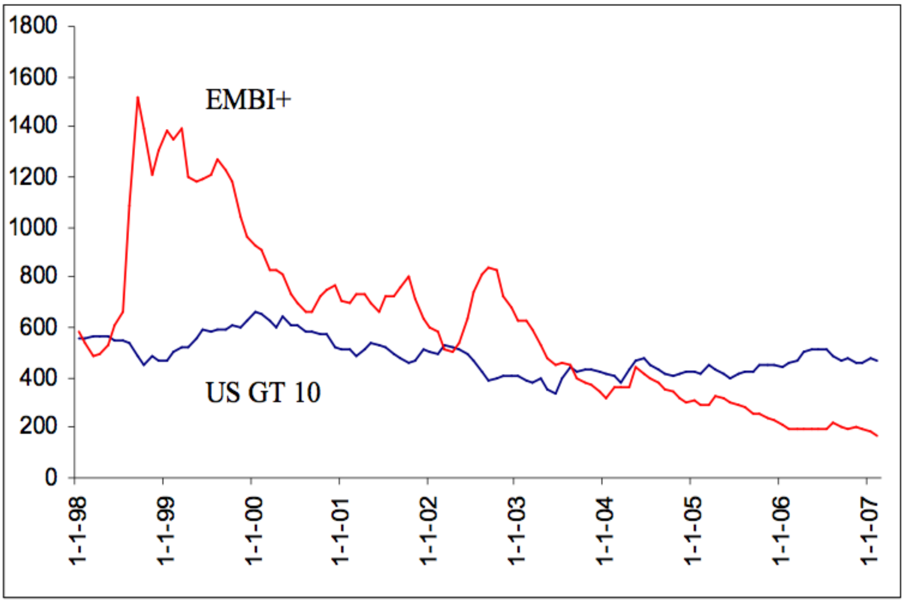
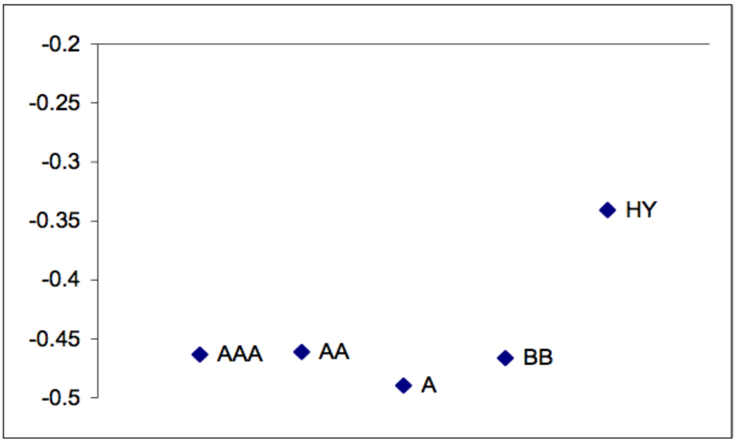


Figure 5.5: Principal Component Analysis

a) Sample I: US Corporate Bond Spreads and EMBI+

(Includes AAA, AA, A, BB, HY and EMBI+ adjusted for Argentina)



b) Sample II: 13 Emerging Market EMBI+ Spreads

(Includes Argentina, Brazil, Mexico, Peru, Venezuela, Ecuador, Panama, Bulgaria,

Morocco, Nigeria, Poland, Russia and Thailand)

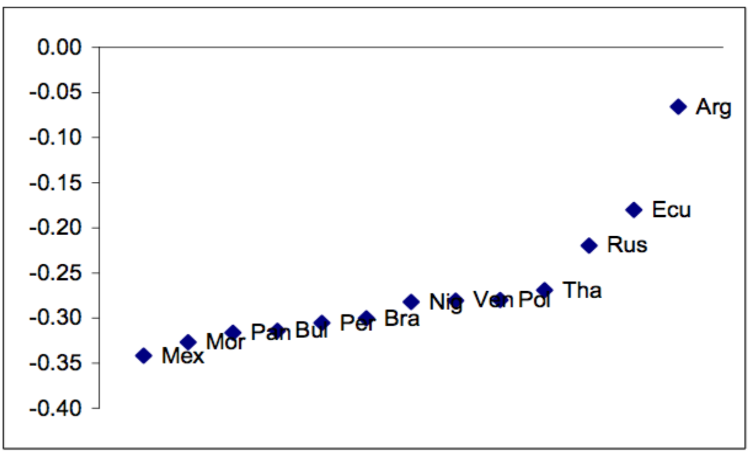


Figure 5.6: First Principal Component for EMBI+ Sample & EMBI+ in differences

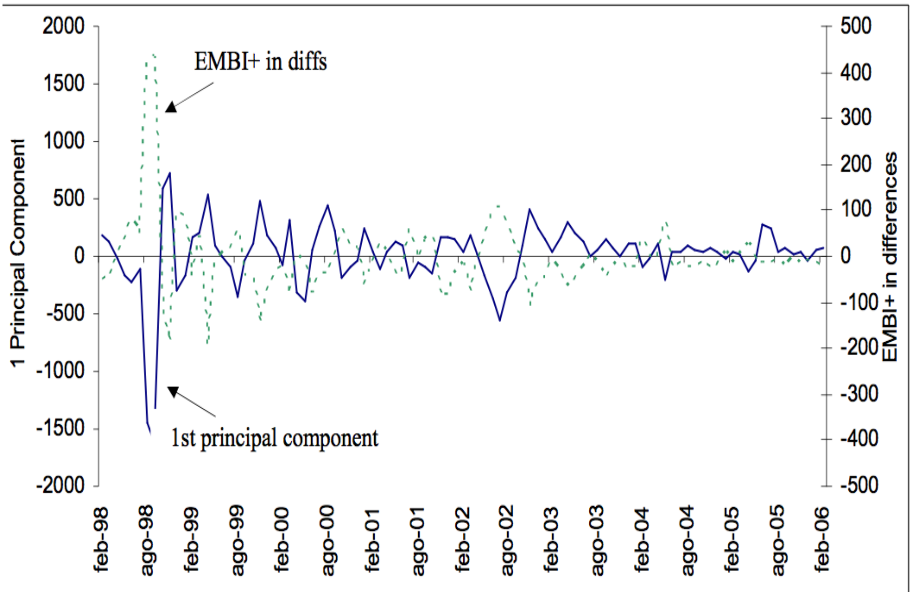
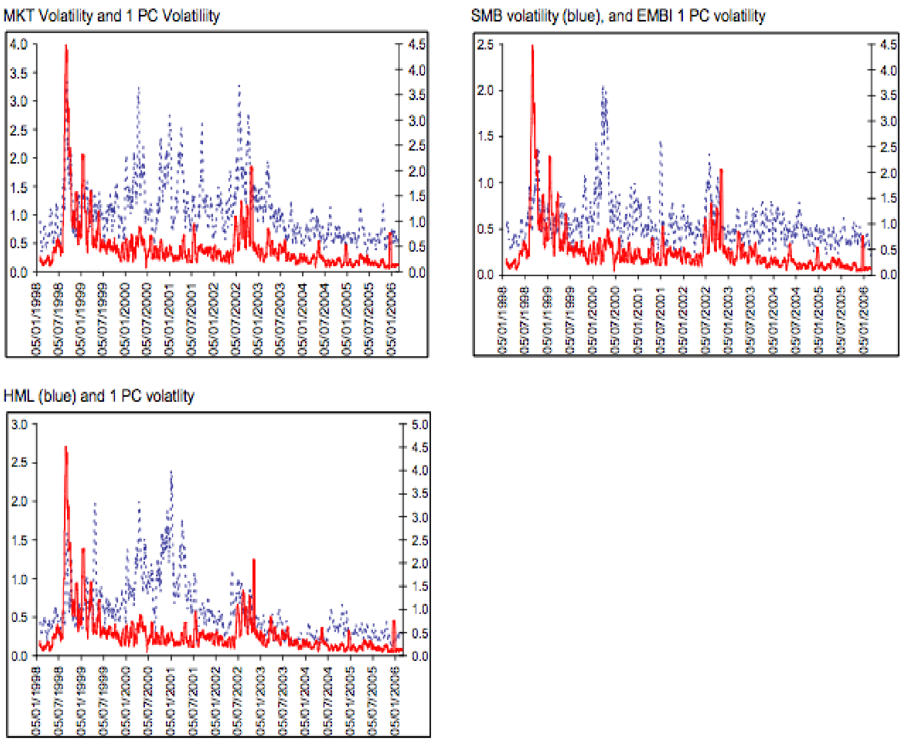


Figure 5.7: Global Investment Appetite and American Fama French Factors (10 day rolling standard deviation)



Bibliography

Abreu, Dilip and Markus K. Brunnermeier, "Bubbles and Crashes," *Econometrica*, January 2003, *71* (1), 173–204.

Aizenman and Marion, "Using Inflation to Erode the U.S. Public Debt," December 2009, (15562).

Amihud, Yakov, "Unexpected Inflation and Stock Returns Revisited - Evidence from Israel," *Journal of Money, Credit, and Banking*, 1996.

Amisano, Gianni and F. Federico, *Alternative Time Varying Parameter Specifications for Bayesian VAR Models.*, Atti della Prima Lezione Mario Arcelli, 2005.

Apergis, Nicholas and Sophia Eleftheriou, "Interest rates, inflation, and stock prices: the case of the Athens Stock Exchange," *Journal of Policy Modeling*, 2002, *24* (3), 231 – 236.

Arora, Vivek and Martin Cerisola, "How Does U.S. Monetary Policy Influence Sovereign Spreads in Emerging Markets?," *IMF Staff Papers*, 2001, *48* (3), 3.

Aruoba, S. Boragan, Christopher J. Waller, and Randall Wright, "Money and capital: a quantitative analysis," *Federal Reserve Bank of St. Louis*, 2009.

Asness, Cliff S, "Fight the Fed Model: The Relationship Between Stock Market Yields, Bond Market Yields, and Future Returns," *SSRN eLibrary*, 2002.

Bai, Jushan and Serena Ng, "Determining the Number of Primitive Shocks in Factor Models," *Journal of Business & Economic Statistics*, January 2007, *25*, 52–60.

Bansal, Ravi and Amir Yaron, "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles," *Journal of Finance*, 08 2004, *59* (4), 1481–1509.

Barr, David G. and John Y. Campbell, “Inflation, Real Interest Rates, and the Bond Market: A Study of UK Nominal and Index-Linked Government Bond Prices,” NBER Working Papers 5821, National Bureau of Economic Research, Inc November 1996.

Barro, Robert J., “Inflationary Finance and the Welfare Cost of Inflation,” *Journal of Political Economy*, Sept.-Oct 1972, *80* (5), 978–1001.

_ , “Rare Events and the Equity Premium,” NBER Working Papers 11310, National Bureau of Economic Research, Inc May 2005.

_ , “Rare Disasters, Asset Prices, and Welfare Costs,” *American Economic Review*, March 2009, *99* (1), 243–64.

_ **and Jose F. Ursua**, “Consumption Disasters in the Twentieth Century,” *American Economic Review*, May 2008, *98* (2), 58–63.

_ **and Tao Jin**, “On the Size Distribution of Macroeconomic Disasters,” Working Paper 15247, National Bureau of Economic Research August 2009.

Bekaert, Geert and Eric Engstrom, “Inflation and the Stock Market:Understanding the "Fed Model",” NBER Working Papers 15024, National Bureau of Economic Research, Inc June 2009.

_ **and** _ , “Inflation and the stock market: Understanding the Fed Model,” *Journal of Monetary Economics*, April 2010, *57* (3), 278–294.

_ **and** _ , “Inflation and the stock market: Understanding the Fed Model,” *Journal of Monetary Economics*, April 2010, *57* (3), 278–294.

_ **,** _ **, and Yuhang Xing**, “Risk, uncertainty, and asset prices,” *Journal of Financial Economics*, January 2009, *91* (1), 59–82.

_ **,** _ **, and** _ , “Risk, uncertainty, and asset prices,” *Journal of Financial Economics*, January 2009, *91* (1), 59–82.

Bianchi, Francesco, "Regime switches, Agents' Beliefs, and Post-World War II U.S. Macroeconomic Dynamics," *Princeton University*, 2009.

Bittlingmayer, George, "Output, Stock Volatility, and Political Uncertainty in a Natural Experiment: Germany, 1880-1940," *Journal of Finance*, December 1998, *53* (6), 2243–2257.

Brandt, Michael W. and Kevin Q. Wang, "Time-varying risk aversion and unexpected inflation," *Journal of Monetary Economics*, October 2003, *50* (7), 1457–1498.

Brennan, Michael J. and Yihong Xia, "Dynamic Asset Allocation under Inflation," *Journal of Finance*, 06 2002, *57* (3), 1201–1238.

Brunnermeier, Markus K. and Christian Julliard, "Money Illusion and Housing Frenzies," NBER Working Papers 12810, National Bureau of Economic Research, Inc December 2006.

Bruno, M. and W. Easterly, "Inflation Crisis and Long-Run Growth," *Journal of Monetary Economics*, 1998, (41), 3–26.

Calvo, Guillermo A., "Explaining Sudden Stops, Growth Collapse and BOP Crises: The Case of Distortionary Output Taxes," NBER Working Papers 9864, National Bureau of Economic Research, Inc July 2003.

_ , "Crises in Emerging Market Economies: A Global Perspective," NBER Working Papers 11305, National Bureau of Economic Research, Inc May 2005.

_ **, Alejandro Izquierdo, and Ernesto Talvi**, "Sudden Stops and Phoenix Miracles in Emerging Markets," *American Economic Review*, May 2006, *96* (2), 405–410.

Cameron, A. Colin and Pravin K. Trivedi, *Microeconometrics Using Stata*, Stata Press, 2009.

Campbell, John Y., "Stock returns and the term structure," *Journal of Financial Economics*, June 1987, *18* (2), 373–399.

__ , "Consumption-based asset pricing," in G.M. Constantinides, M. Harris, and R. M. Stulz, eds., *Handbook of the Economics of Finance*, Vol. 1 of *Handbook of the Economics of Finance*, Elsevier, March 2003, chapter 13, pp. 803–887.

__ **and John Ammer**, "What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns," *Journal of Finance*, March 1993, *48* (1), 3–37.

__ **and John Cochrane**, "Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior," *Journal of Political Economy*, April 1999, *107* (2), 205–251.

__ **and Luis M. Viceira**, "Consumption And Portfolio Decisions When Expected Returns Are Time Varying," *The Quarterly Journal of Economics*, May 1999, *114* (2), 433–495.

__ **and Robert J. Shiller**, "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies*, 1988, *1* (3), 195–228.

__ **and** __ , "Stock Prices, Earnings, and Expected Dividends," *Journal of Finance*, July 1988, *43* (3), 661–76.

__ **and** __ , "A Scorecard for Indexed Government Debt," in "NBER Macroeconomics Annual 1996, Volume 11" 1996.

__ **and Tuomo Vuolteenaho**, "Inflation Illusion and Stock Prices," *American Economic Review*, May 2004, *94* (2), 19–23.

Carrieri, Francesca and Basma Majerbi, "The pricing of exchange risk in emerging stock markets," *Journal of International Business Studies*, May 2006, *37* (3), 372–391.

Cecchetti, Stephen G., Alfonso Flores-Lagunes, and Stefan Krause, "Has Monetary Policy become more Efficient? a Cross-Country Analysis," *Economic Journal*, 04 2006, *116* (511), 408–433.

— , **Lam, and Nelson C. Mark**, "Asset Pricing with Distorted Beliefs: Are Equity Returns Too Good to Be True?," *American Economic Review*, September 2000, *90* (4), 787–805.

— , **Margaret M McConnell, and Gabriel Perez-Quiros**, "Policymakers' Revealed Preferences and the Output-Inflation Variability Trade-Off: Implications for the European System of Central Banks," *Manchester School*, Special I 2002, *70* (4), 596–618.

Chari, V. V., Lawrence J. Christiano, and Patrick J. Kehoe, "Optimality of the Friedman rule in economies with distorting taxes," *Journal of Monetary Economics*, April 1996, *37* (2-3), 203–223.

Chen, Long and Xinlei Zhao, "Return Decomposition," *SSRN eLibrary*, 2008.

Chiarella, Carl, Chih-Ying Hsiao, and Willi Semmler, "Intertemporal Investment Strategies under Inflation Risk," Research Paper Series 192, Quantitative Finance Research Centre, University of Technology, Sydney January 2007.

Clauset, Aaron, Cosma Rohilla Shalizi, and M. Newman, "Power-law distributions in empirical data," 2009.

Cline, William R and Kevin J Barnes, "Spreads and Risk in Emerging Markets Lending," *Institute of International Finance, IIF Research Papers*, 1997, *No. 97-1.*

Cogley, Timothy and Thomas J. Sargent, "The market price of risk and the equity premium: A legacy of the Great Depression?," *Journal of Monetary Economics*, 2008, *55* (3), 454 – 476.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, "Money Illusion in the Stock Market: The Modigliani-Cohn Hypothesis," *Quarterly Journal of Economics*, 2005, *120* (2), 639–668.

Collin-Dufresne, Pierre, Robert S. Goldstein, and Jean Helwege, "Is Credit Event Risk Priced? Modeling Contagion via the Updating of Beliefs," NBER Working Papers 15733, National Bureau of Economic Research, Inc February 2010.

Cooley, Thomas F and Gary D Hansen, "The Inflation Tax in a Real Business Cycle Model," *American Economic Review*, September 1989, *79* (4), 733–48.

Danthine, Jean-Pierre and John B. Donaldson, "Inflation and Asset Prices in an Exchange Economy," *Econometrica*, 1986, *54* (3), 585–605.

Dornbusch, Rudiger, "Stopping Hyperinflation: Lessons from the German Inflation Experience of the 1920s," November 1987, (1675).

Drukker, D., P. Gomis-Porqueras, and P. Hernandez-Verme, "Threshold Effects in the Relationship Between Inflation and Growth: A New Panel-Data Approach," *working paper*, 2005.

Duarte, Fernando M, "Inflation Risk and the Cross Section of Stock Returns," *Technology*, 2010, (857).

Dungey, Mardi, Renee Fry, Vance Martin, and Brenda Gonzalez-Hermosillo, "Characterizing Global Investors' Risk Appetite for Emerging Market Debt During Financial Crises," IMF Working Papers 03/251, International Monetary Fund January 2004.

Durre, Alain and Pierre Giot, "An International Analysis of Earnings, Stock Prices and Bond Yields," *Journal of Business Finance & Accounting*, 2007, *34* (3-4), 613–641.

Edwards, Sebastian, "The pricing of bonds and bank loans in international markets : An empirical analysis of developing countries' foreign borrowing," *European Economic Review*, June 1986, *30* (3), 565–589.

Eichengreen, Barry and Ashoka Mody, "What Explains Changing Spreads on Emerging-Market Debt: Fundamentals or Market Sentiment?," NBER Working Papers 6408, National Bureau of Economic Research, Inc February 1998.

Embrechts, P., C. Kluppelberg, and T. Mikosch, *Modelling Extremal Events for Insurance and Finance*, Spriger, Berlin, 1997.

Esscher, Fredrik, "On the probability function in the collective theory of risk," *Scandinavian Actuarial Journal*, 1932, *15* (175-195.).

Fama, Eugene F, "Stock Returns, Real Activity, Inflation, and Money," *American Economic Review*, September 1981, *71* (4), 545–65.

_ **and G William Schwert**, "Inflation, Interest, and Relative Prices," *Journal of Business*, April 1979, *52* (2), 183–209.

_ **and Kenneth R French**, "The Cross-Section of Expected Stock Returns," *Journal of Finance*, June 1992, *47* (2), 427–65.

_ **and Kenneth R. French**, "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, February 1993, *33* (1), 3–56.

Feldman, Gerald D., *The Great Disorder: Politics, Economics, and Society in the German Inflation, 1914-1924*, Oxford University Press, 1997.

Felices, Guillermo, Christian Grisse, and Jing Yang, "International financial transmission: emerging and mature markets," Bank of England working papers 373, Bank of England August 2009.

Fernandez-Arias, Eduardo, "The new wave of private capital inflows: Push or pull?," *Journal of Development Economics*, March 1996, *48* (2), 389–418.

Fischer, Stanley, Ratna Sahay, and Carlos A. Vegh, "Modern Hyper- and High Inflations," *Journal of Economic Literature*, September 2002, *40* (3), 837–880.

Fisher, Irving, *Money Illusion*, Adelphi, 1928.

Frenkel, Jacob A, "The Forward Exchange Rate, Expectations, and the Demand for Money: The German Hyperinflation," *American Economic Review*, September 1977, *67* (4), 653–70.

Friedman, Milton, "Government Revenue from Inflation," *Journal of Political Economy*, July-Aug. 1971, *79* (4), 846–56.

_ , "Nobel Lecture: Inflation and Unemployment," *Journal of Political Economy*, June 1977, *85* (3), 451–72.

Fuentes, Mónica and Sergio Godoy, "Sovereign Spread in Emerging Markets: A Principal Component Analysis," Working Papers Central Bank of Chile 333, Central Bank of Chile November 2005.

Gabaix, Xavier, "Variable Rare Disasters: A Tractable Theory of Ten Puzzles in Macro-finance," *American Economic Review*, May 2008, *98* (2), 64–67.

García-Herrero, Alicia and Álvaro Ortiz, "The role of global risk aversion in explaining Latin American sovereign spreads," Banco de España Working Papers 0505, Banco de España February 2005.

Geske, Robert and Richard Roll, "The Fiscal and Monetary Linkage Between Stock Returns and Inflation," *The Journal of Finance*, 1983, *38* (1), 1–33.

Gollier, Christian, "Time Horizon and the Discount Rate," *Journal of Economic Theory*, December 2002, *107* (2), 463–473.

_ **and Harris Schlesinger**, "Changes in risk and asset prices," *Journal of Monetary Economics*, May 2002, *49* (4), 747–760.

González-Rozada, Martín and EduardoLevy Yeyati, "Global Factors and Emerging Market Spreads," *Economic Journal*, November 2008, *118* (533), 1917–1936.

Gourio, Francois, "Disasters and Recoveries," *American Economic Review*, May 2008, *98* (2), 68–73.

Grandes, Martín, "The Determinants of Sovereign Bond Spreads: Theory and Facts From Latin America," *Latin American Journal of Economics-formerly Cuadernos de Economía*, 2007, *44* (130), 151–181.

Hansen, Bruce E., "Threshold effects in non-dynamic panels: Estimation, testing, and inference," *Journal of Econometrics*, 1999, *93* (2), 345 – 368.

_ , "Sample Splitting and Threshold Estimation," *Econometrica*, 2000, *3* (68), 575–603.

Hansen, Lars Peter and Kenneth J Singleton, "Stochastic Consumption, Risk Aversion, and the Temporal Behavior of Asset Returns," *Journal of Political Economy*, April 1983, *91* (2), 249–65.

Hardy, Mary, *Investment guarantees: modeling and risk management for equity-linked life insurance*, Wiley, 2003.

Joutz, Chao Wei; Fred, "Inflation Illusion or No Illusion: What did Pre- and Post-War Data Say?," 2007.

Kaminsky, Graciela L., Carmen M. Reinhart, and Carlos A. Vegh, "The Unholy Trinity of Financial Contagion," *Journal of Economic Perspectives*, Fall 2003, *17* (4), 51–74.

Khan, M. and A.S. Senhadji, "Threshold effects in the Relationship between Inflation and Growth," *IMF Staff Papers*, 2001, *48*.

Laeven, Luc A. and Fabian V. Valencia, "Systemic Banking Crises: A New Database," *SSRN eLibrary*, 2008.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, "A skeptical appraisal of asset pricing tests," *Journal of Financial Economics*, May 2010, *96* (2), 175–194.

McGuire, Patrick and Martijn A Schrijvers, "Common factors in emerging market spreads," *BIS Quarterly Review*, December 2003.

Merton, Robert C, "An Intertemporal Capital Asset Pricing Model," *Econometrica*, September 1973, *41* (5), 867–87.

Min, Hong G., "Determinants of emerging market bond spread : do economic fundamentals matter?," Policy Research Working Paper Series 1899, The World Bank March 1998.

Modigliani, Franco and Richard A. Cohn, "Inflation, Rational Valuation And The Market," *Financial Analysts Journal*, March/Apri 1979, *35* (2), 24–44.

Nelsen, R.B., *An Introduction to Copulas*, Springer, New York, 2006.

Ng, Serena and Sydney C. Ludvigson, "A Factor Analysis of Bond Risk Premia," *Department of Economics, New York University*, 2009.

Pastor, Lubos and Pietro Veronesi, "Was there a Nasdaq bubble in the late 1990s?," *Journal of Financial Economics*, July 2006, *81* (1), 61–100.

_ **and Veronesi Pietro**, "Stock Valuation and Learning about Profitability," *Journal of Finance*, October 2003, *58* (5), 1749–1790.

Patton, A, "Copula-based models for financial time series," *Handbook of Financial Time Series*, 2009.

Pennacchi, G., "Identifying the Dynamics of Real Interest Rates and Inflation: Evidence Using Survey Data," *Review of Financial Studies*, 1991, *4*, 53–86.

Pereira-Garmendia, Diego, "The Stock Price-Inflation Puzzle: New Evidence," *working paper*, 2008.

Petkova, Ralitsa, "Do the Fama-French Factors Proxy for Innovations in Predictive Variables?," *Journal of Finance*, 04 2006, *61* (2), 581–612.

Piaskowski, Wojtek, "Pricing and Risk Analysis of Maturity Guarantees Embedded in the Retirement Investment Products - Markov Switching Approach," 2005.

Rajan, Raghuram G and Luigi Zingales, "Financial Dependence and Growth," *American Economic Review*, June 1998, *88* (3), 559–86.

Rietz, Thomas A., "The equity risk premium a solution," *Journal of Monetary Economics*, July 1988, *22* (1), 117–131.

Ritter, Jay R. and Richard S. Warr, "The Decline of Inflation and the Bull Market of 1982-1999," *The Journal of Financial and Quantitative Analysis*, 2002, *37* (1), 29–61.

Salomons, Roelof and Henk Grootveld, "The Equity Risk Premium: Emerging versus Developed Markets," *Emerging Markets Review*, 2003, *Vol. 4*, 121–144.

Santis, Massimiliano De, "Movements in the Equity Premium: Evidence from a Time Varying VAR," *SSRN eLibrary*, 2004.

Schmeling, Maik and Andreas Schrimpf, "Expected Inflation, Expected Stock Returns, and Money Illusion: What can we learn from Survey Expectations?," May 2008, (SFB649DP2008-036).

Shafir, Eldar, Peter Diamond, and Amos Tversky, "Money Illusion," *The Quarterly Journal of Economics*, 1997, *112* (2), 341–374.

Sløk, Torsten and Mike Kennedy, "Factors Driving Risk Premia," OECD Economics Department Working Papers 385, OECD Publishing April 2004.

Smith, David C., "Finite sample properties of tests of the Epstein-Zin asset pricing model," *Journal of Econometrics*, November 1999, *93* (1), 113–148.

Spyrou, S. I., "Are stocks a good hedge against inflation? evidence from emerging markets," *Applied Economics*, January 2004, *36* (1), 41–48.

Stock, James H. and Mark W. Watson, "Has the business cycle changed?," *Proceedings*, 2003, pp. 9–56.

Thomas, J. and F. Zhang, "Don't Fight the Fed model," *Yale University working paper.*, 2008.

Timmermann, Allan, "Structural Breaks, Incomplete Information, and Stock Prices," *Journal of Business & Economic Statistics*, July 2001, *19* (3), 299–314.

Turroni, Costantino Bresciani, *The Economics of Inflation: A Study of Currency Depreciation in Post-War Germany* ISBN 0415313929, 9780415313926, Routledge, 2003.

Uribe, Martin and Vivian Z. Yue, "Country spreads and emerging countries: Who drives whom?," *Journal of International Economics*, June 2006, *69* (1), 6–36.

Voth, Hans-Joachim, "With a Bang, not a Whimper: Pricking Germany's in 1927 and the Slide into Depression," *The Journal of Economic History*, March 2003, *63* (01), 65–99.

Wachter, Jessica, "Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility?," Working Paper 14386, National Bureau of Economic Research October 2008.

Webb, Melanie Ann, "A Switching Black-Scholes Model and Option Pricing." PhD dissertation, The University of Adelaide 2003.

Webb, Steven Benjamin, *Hyperinflation and stabilization in Weimar Germany* ISBN 0195052943, 9780195052947, Oxford university press, 1989.

Weder, Mark, "A heliocentric journey into Germany's Great Depression," *Oxford Economic Papers*, April 2006, *58* (2), 288–316.

_ , "Some Observations on the Great Depression in Germany," *German Economic Review*, 02 2006, *7*, 113–133.

Wei, Chao, "Does the Stock Market React to Unexpected Inflation Differently Across the Business Cycle?," 2007.

Xiong, Wei and Hongjun Yan, "Heterogeneous Expectations and Bond Markets," *Review of Financial Studies*, 2009.

Zhang, Frank and Jacob Thomas, "Don't fight the Fed Model! Don't fight the Fed Model!," 2008.

A APPENDICES

APPENDIX I.1

Panel-Threshold-Estimation

This section presents the Hansen (1999) panel threshold model. The equation to estimate is:

$$y_{it} = \alpha_i + \beta_1' x_{it} I(q_{it} \leq \gamma) + \beta_2' x_{it} I(q_{it} > \gamma) + \varepsilon_{it} \qquad \text{(A.1)}$$

where $I(\centerdot)$ is an indicator function. The error term ε_{it} is independent and identically distributed with zero mean and finite variance σ^2. The subscript i stands for the cross-sections with $1 \leq i \leq N$ and t indexes time ($1 \leq i \leq T$). The dependent variable y_{it} and the threshold variable q_{it} are scalar, the regressor x_{it} is a k-dimensional vector of exogenous variables. Note that x_{it} may contain variables with slope coefficients constrained to be the same in the two regimes which have no effects on the distribution theory. If the threshold variable q_{it} is below or above a certain value of q_{it}, in this case γ, the regressor x_{it} has a different impact on y_{it}. In other words, $\beta_1 \neq \beta_2$. It is worth to emphasize that the threshold variable q_{it} may be an element of x_{it}.

In order to estimate the model, I follow Hansen (1999, 2000), who follows a fixed effects approach. First, restate Equation 1 as:

$$y_{it} = \alpha_i + \beta' x_{it}(\gamma) + \varepsilon_{it} \qquad \text{(A.2)}$$

where $x_{it}(\gamma) = \begin{pmatrix} x_{it} I(q_{it} \leq \gamma) \\ x_{it} I(q_{it} > \gamma) \end{pmatrix}$ and $\beta = \begin{pmatrix} \beta_1' & \beta_2' \end{pmatrix}'$. The OLS estimation of β is:

$$\hat{\beta}(\gamma) = \left(X^*(\gamma)' X^*(\gamma) \right)^{-1} X^*(\gamma)' Y^* \qquad \text{(A.3)}$$

where X^*, Y^* are defined as $X^* = X - \bar{X}$, $Y^* = Y - \bar{Y}$.

The sum of squared errors can be written as

$$S_1(\gamma) = \hat{\varepsilon}^*(\gamma)' \hat{\varepsilon}^*(\gamma) = Y^{*'} \left(I - X^*(\gamma)' \left(X^*(\gamma)' X^*(\gamma) \right)^{-1} X^*(\gamma) X^*(\gamma)' \right) Y^* \tag{A.4}$$

Thus, for each γ there is a sum of squared errors. We find $\hat{\gamma}$ as the one that minimizes the sum of squared errors.

Thus,

$$\hat{\beta} = \hat{\beta}(\hat{\gamma}) \tag{A.5}$$

$$\hat{\sigma^2} = \frac{1}{N(T-1)} S_1(\hat{\gamma}) \tag{A.6}$$

APPENDIX I.2

How Much of the Real Stock Price Variation is Explained by Decreasing Earning Growth Rates?

Having quantified the impact of inflation on earnings, now the aim is to quantify how much of the variation in earnings yield is explained by inflation only affecting real earning growth rates. This is done in two different ways. First, I calibrate asset-pricing models, assuming that inflation only affects real earning growth rates. I the compare the predicted real stock price variation to the actual variation of real stock prices.

In a second step, I perform simulations in order to find the predicted variation in real stock prices. There are three dimensions to be taken into account to capture the effect of inflation on real earning growth rates: i) the quantitative impact impact of inflation on real earnings; ii) the duration of the inflation spell; and iii) the monthly inflation distribution. Having the probability distribution for each of these dimensions -the marginal distributions-, copulas are used to get the multivariate distribution of the shocks. Once the real earning growth rate is simulated, the predicted variation in earning yield is compared to the actual variation.

Evidence from Asset-Pricing Models

I calibrate three asset pricing models discussed in Pastor and Veronesi (2006). Assuming that inflation only affects real earning growth rates, the predicted variation in earnings price ratios for a given inflation shock are compared to the actual variation in earnings price ratios[1].

[1] While Pastor and Veronesi (2006) work with dividend yields, I assume earnings and dividend to be equivalent for the valuation exercises that are performed in

Note that the variation predicted by each model is only explained by inflation affecting real earning growth rates, while the actual variation maybe caused by inflation affecting risk as well. Thus, the share of predicted model variation over the actual earning yield variation can be understood as the share of the real stock price variation explained by inflation affecting real earnings:

$$\frac{\triangle \frac{E}{P}^{P}}{\triangle \frac{E}{P}^{A}} = \frac{predicted\ variation}{actual\ variation} = share\ explained\ by\ decreasing\ earnings$$

I proceed as follows. First, the earning yield models described below are calibrated for EMs. For that, I use sample mometnts: the annualized average real earning growth rate (0.084) [2], and the average earning yield (0.087). In Section 3, the annual impact on inflation on real earning growth rate is quantified (-1.3 percent). Moreover, the estimation results show that the inflation spell duration is on average 12 months. All the calculations are done for a five percent (annualized) inflation rate. For an annualized 5 percent inflation rate, the actual variation in the earning yield is 0.019.

Model 1: No Uncertainty

The first model to calibrate is the Gordon model under no uncertainty. In this first approximation we are ruling out uncertainty, and take the effect of inflation on earning growth rates as perfectly known. The earnings price relation follows

this section. Since I'm interested in valuation changes, any constant introduced to acommodate the earning-diviend relation disappears.

[2]For the calculations I use 10-sector-country averages for earning growth rates and the estimated variations coming for sector-country regressions.

$$\frac{E}{P} = r_f + r_p - g$$

where r_f is the risk free rate, r_p is the risk premium, and g is the earning growth rate.

Using the parameters in Panel A of Table **??**, the risk premium is derived, such that the sample average earning yield is matched. The implicit premium (r_p) is 11.8 percent, which is close to the value reported in Salomons and Grootveld (2003)[3]. Using the 11.8 percent premium plus the five percent risk free rate, a permanent impact of a five percent inflation shock predicts a 0.013 bps increase in the earning yield, which explains a 849 percent of the actual variation. However, from Section 3 we know that the impact of inflation is not permanent, as the average inflation spell duration is 12 months. Taking this into account, the model is able to predict a 5.1 percent of the actual variation in earning yield.

Model 2: Uncertainty on Earning Growth Rates

Uncertainty is introduced by introducing volatility of earning growth rates in the stochastic discount factor. The earning yield can now be expressed as

$$\frac{E}{P} = r_f - (1 - \lambda\,\gamma)\,g + 0.5\,\lambda\,\gamma\,(1 - \lambda\,\gamma)\,\sigma_e^2$$

where the parameters λ is the share of earning consumption and γ is risk aversion. Following Pastor and Veronesi (2006), these parameters take the values 0.33 and 2, , respectively[4]. The risk free rate is

[3]On an equal weighted basis, Salomons and Grootveld (2003) report an annualised excess risk premium of the EMs is 12.7% for the 1985-2001 period. However, the market-weighted index for EMs presents an annualised premium of 3.1% for the period.

[4]Whether these coefficients are the ones to use in the case of EM is debatable.

calibrated, such that for the given set of parameters, the earning yield matches the sample earning yield value (0.087) and earning growth rate unconditional volatility (0.36). The implicit risk free rate in this case is 0.1045, lower than the 0.168 rate in Model 1 (risk free plus risk premium), as expected.

Would the inflation effect on real earnings be permanent, the model predicts the earning yield to increase almost five times the actual variation. However, when inflation spell has a one-year duration, the predicted variation explains 11 percent of the actual variation. Thus, adding uncertainty on earnings growth rates increases almost twice the explained variation.

I repeat the exercise using the conditional volatility of real earning growth rates. When inflation is above the 5 percent annualized rate, the standard deviation of real earning growth rate is 0.39, significantly higher than the unconditional figure (0.36). Incorporating this increase in uncertainty increased the explained variation up to 16 percent. In order to explain a 100 percent of the observed inflation, the standard deviation of earning growth rates should increase up to 0.7, almost two times the unconditional standard deviation and well above the 0.39 conditional standard deviation. Thus, while it is true that uncertainty increases the share of predicted over actual variation, there is still an 84 percent left unexplained.

Model 3: Uncertainty on Both Inflation and Earning Growth Rates

A second dimension of uncertainty is included in the model. While uncertainty over real earning growth rates is already incorporated in

However, changing these coefficients does not change the final results in a significant way.

Model 2, now I add uncertainty over the inflation rate itself[5]. The earning yield can be written in a similar way as Model 2[6]

$$\frac{E}{P} = \frac{-g + r_f - \gamma \sigma_e^2 + V_\theta \left(1+\gamma\right)}{1+k}$$

where the term V_θ, which is negative, is meant to capture the degree of uncertainty about the expected inflation rate. As discussed above, an increase in the absolute value of V_θ drives stock prices upwards. The term k[7] is to be calibrated from the data. As a proxy for V_θ, I use the standard deviation of expected inflation rates. For that, I work with the Professional Forecasters Survey data for the US. In the 80s, when inflation peaked, a five percent increase in realized inflation increases the standard deviation of expected inflation by 281 percent. After finding k, the steps in Model 1 and 2 are repeated. The results show that, when including uncertainty over future inflation rates, the predicted variation in earning growth rates jumps to 17 percent of the actual variation. When using the conditional volatility of earning growth rates, the explained share increase to 19 percent.

Taken together, the results in Table**??** highlight the importance of earning variations when explaining real stock price variations for a

[5] As shown in Pastor and Veronesi (2006), Pastor and Pietro (2003), uncertainty over future inflation rates would increase the stock price as agents increase the demand for the stock, given the upward value of earnings in the bad state of nature. The higher the risk aversion, the higher the impact of this uncertainty dimension on the stock price.

[6] This expression is in the technical appendix of Pastor and Veronesi (2006).

[7] Following Pastor and Veronesi, I define the term k as: $k = p\sum_i c_i\left(f_i - \pi_i\right)$, where p is the stock price, c_i, f_i, π_i are consumption, and probability of state i. This term is calibrated from the data.

given inflation shock. Between 5 and 20 percent of the actual earning yield variation is explained, depending on the model. While this share may seem low, it is worth to emphasize that in the literature this share is found to be zero or even negative (meaning inflation correlating positively with earnings and dividends).

Evidence from Copula Simulations

Another way to quantify the importance of decreasing earnings on the real stock price variation is to aggregate all the information learnt in previous sections in an unique distribution. There are three density functions that are relevant for the effect of inflation on real earning growth rates: i) the distribution for the impact of inflation on real earnings; ii) the distribution of the inflation spell duration; and iii) the distribution for the monthly inflation rates. In order to work with these marginal distributions at a time, I need a way to summarize the dependence properties of the data. A copula approach is suitable for that matter[8]. The dependence structure gives the probability that multiple assets will be at their extreme lows of heights at the same time. Note the importance of choosing correctly the copula to use. In relation to our problem, it is known that the inflation spell is longer when monthly inflation rates are higher and when the impact of inflation on real earnings is stronger. In order to capture the dependence, a Gumbel copula is the best option. However, it is also true than the opposite happens for the lower tails (lower inflation rates, shorter spell and weak inflation impact). In this case, a Clayton copula is the one to use, as it shows greater dependence in the lower tail than in the upper tail. Below, the pricing model used for the simulations is described, as the relevant distributions and the results from the simulations.

[8] The literature on copula methods in extensive. However, good introductions can be found in Nelsen (2006), Embrechts et al. (1997) and Patton (2009)

Pricing Model and Marginal Distributions

For simulations, I work with asset-pricing Model 2. In the model, the volatility of earning growth rates is included in the stochastic discount factor. The earning yield takes the following form:

$$\frac{E}{P} = r_f - (1 - \lambda\,\gamma)\, g + 0.5\,\lambda\,\gamma\,(1 - \lambda\,\gamma)\,\sigma_e^2 \qquad \text{(A.7)}$$

where r_f is the risk-free rate, λ is the share of earnings consumed in the period, γ is the risk aversion parameter, g is the earning growth rate and σ_e is the standard deviation of the earning growth rate. I calibrate the risk free rate such that the earning yield matches the sample average earning yield value (0.087) and earning growth rate volatility (0.36). The aim of the exercise is to simulate g, which distribution depends on: i) the distribution for the impact of inflation on real earnings; ii) the distribution of the inflation spell duration; and, iii) the distribution of the monthly inflation rates. The distribution i) and ii) are assumed Normal, with mean and standard deviation as in Table **??**. The first and second moments are chosen so to match the empirical findings in Section 3. The distribution of inflation used is the empirical one, estimated following a kernel density estimation procedure.

Simulations and Results

We know that the three distributions are positively correlated on the right tail. That is, the probability of having a strong impact of inflation on real earnings increases if the inflation rate is high; and the probability of observing a longer inflation spell increases if the inflation rate is high. In order to incorporate this dependence structure in the exercise, I perform a copula simulation using the Gumbel Archimedean copula. The Gumbel copula is useful since it exhibits stronger dependence in the upper tail than in the lower tail.

I draw values from the distributions for i) the impact of inflation on real earnings; ii) the inflation spell duration; and, iii) the monthly inflation rates; and the random variate (u_1, u_2, u_3) from the Gumbel copula, and find the predicted earning growth rate $g*$. At the same time, using the results in Section 3, the actual change in earnings price for the inflation rate draw in iii) is calculated. The procedure is repeated 10,000 times.

I compare the average change in the earnings price coming from the simulations (predicted variation) with the average actual change (actual variation). The results are presented in Table **??**. The share of predicted over actual variation is between 18 and 21 percent, depending on the Gumbel copula parameter. The table also includes the results when working with a Clayton copula. In this case, there is a greater dependece in the lower tail than in the upper tail. In this last case the results are between 8 and 9 percent.

The conclusion from this section is that falling real earning growth rates explain a significant share of the observed earning yield variation. The explained share is close to 20 percent, as the Gumbel copula approach appears to be the most appropriate estimation method. While this share may seem low, it is worth to remind the reader that in the literature the share is found to be close to zero or even negative (meaning inflation correlating positively with earnings and dividends). With respect to the unexplained 80 percent of the earning yield variation, the results presented in Sections 3 point in the direction of a positive correlation between inflation and higher uncertainty and risk aversion (see Bekaert et al. 2009b, **?**). It is true that without quantifying the risk-inflation relation, money illusion can not be discarded when explaining the inflation-real stock price relation. However, most of the behavioral theories rely on a relevant share of the earning yield variation that remains unexplained by the correlation of inflation and real earnings (or dividends). Being this share close to 20 percent in the case of EMs, it seems that the room for behavioral theories is, at least, reduced.

Table 1: How Much of the Real Stock Price Variation is Explained by Decreasing Earnings?

Notes: I infer the share of the earnings price variation explained by inflation affecting only real earning growth rates. To do so, I calibrate three asset pricing models from Pastor and Veronesi (2006), and compare the predicted variation coming from inflation decreasing earnings with the actual variation in earnings price ratios. In Panel A, I present the input data for the exercise. In Panel B, I present the variation predicted by each pricing model when inflation decreases real earning growth rates. The inflation spell duration is one year. For each model , I also present the predicted variation over the actual earning yield variation: $\frac{\triangle \frac{E}{P}^{P}}{\triangle \frac{E}{P}^{A}} = \frac{predicted\ variation}{actual\ variation}$. Model 1 is the Gordon model without uncertainty. Model 2 includes uncertainty on earning growth rates. In Column i), the unconditional standard deviation of earning growth rates is used (0.36), while in Column ii) the conditional standard deviation of earning growth rates is used (0.39). Model 3 includes uncertainty over future inflation rates. In the model, higher uncertainty over expected inflation rates increase the stock prices, as the marginal valuation of earnings increases the higher the risk aversion coefficient. * Variation conditional on a 5 percent annualized inflation shock

Panel A: Sample Data

Average E/P in sample	0.087
Average real Earning Growth Rate	0.084
Inflation shock (annualized)	0.050
12-Month Decrease in Real Earning Growth Rates *	0.013
Increase in E/P *	0.019

Panel B: Effect of 5% Inflation Shock on Real Stock Prices

Model 1

Predicted EP variation	0.0000780
$\frac{\triangle \frac{E}{P}^{P}}{\triangle \frac{E}{P}^{A}}$	5.11%

Model 2

	i) Unconditional Uncertainty	***ii) Conditional Uncertainty***
Predicted EP variation	0.000168	0.000246
$\frac{\triangle \frac{E}{P}^{P}}{\triangle \frac{E}{P}^{A}}$	10.98%	16.04%

Model 3

	i) Unconditional Uncertainty	***ii) Conditional Uncertainty***
Predicted EP variation	0.00026	0.00029
$\frac{\triangle \frac{E}{P}^{P}}{\triangle \frac{E}{P}^{A}}$	17.14%	18.99%

Table 2: Copula Approach: Marginal Distributions

Notes: The table shows the first and second moments of the following marginal distributions: i) the distribution for the impact of inflation on real earnings; ii) the distribution of the inflation spell duration; and, iii) the distribution for the monthly inflation rates. This last distribution is estimated using kernel density estimation (see Figure 1). The mean and standard deviations for i) and ii) are chosen so to match the estimations of the paper.

	Distribution	Mean	St. Deviation
Inflation Spell	Normal	12.0000	4.0000
Impact on Real Earnings	Normal	3.1900	1.5000
Inflation	Empirical	0.0171	0.0567

Table 3: Copula Approach: Results

Notes: The table shows the Archimedean copula family used to simulate the variations in earning yields when inflation affects real earning growth rates. The theta coefficient is the parameter used in every estimation for the random variate (u_1, u_2, u_3). The $\frac{\triangle \frac{E}{P}^P}{\triangle \frac{E}{P}^A}$ column presents the predicted earning yield variation over the actual variation.

Copula	Theta	$\frac{\triangle \frac{E}{P}^P}{\triangle \frac{E}{P}^A}$
	2.0	0.21
Gumbel	2.5	0.18
	3.0	0.19
	2.0	0.08
Clayton	2.5	0.09
	3.0	0.09

APPENDIX V.1

This section deals with the integration of two markets whose agents might have different expectations on the way some shocks impact on each other fundamentals. The idea comes from an heterogeneous agent models in which there are heterogeneous beliefs. This is borrowed from Xiong and Yan (2009), with minor differences for the sake of simplicity, and is only included to show some of the intuition.

There are different ways in which to model heterogeneous beliefs (different initial beliefs, different learning processes, etc). I do not enter in this discussion, I just incorporate the possibility of agents to have different a priori beliefs on how a shock might impact expected returns. For example, one shock can be interpreted by agent i as causing an increase in the probability of default of agent j, while j herself might believe the same shock is irrelevant to her own default probabilities.

This framework is able to capture unexpected behavior from some countries related to exogenous shocks, i.e.: sudden stops a la Calvo. For instance, non Brazilian or Chilean forecaster believed that a crisis in Russian could hit their countries as it did, while some agents in the central financial markets obviously sold these countries debt due to the financial distress in Russia.

Since I'm not interested in how to model this particular heterogeneity, I just assume that the agents (countries) are heterogenous meaning that each one has its own probability measure set.

The Model

Assume then that there are two agents (countries), developed and emerging. Both have logarithmic utility functions for the sake of simplicity. The logarithmic utility function will enable to work in a very easy way with the probabilities of different state of nature of each country, since they are going to be equal to their relative wealth, as shown below.

For agent j, and given the log utility functions, the relationship derived from the first order condition between consumption and wealth is:

$$c_t^j = \beta W_t^j, \quad j = 1,2 \tag{A.8}$$

Now, an asset exists which expected payoff is X_t, with $X_t < \infty$. Then we can define another asset with expected payoff y_t, which relates to agent 1 wealth, and is defined as

$$y_t = \frac{W_{t+1}^1}{W_t^1} X_t \tag{A.9}$$

The corresponding pricing equation for this last asset with expected payoff y_t is

$$P(y_t) = E_t^1 \left[\frac{U'(c_{t+1})}{U'(c_t)} y_t \right] \tag{A.10}$$

Using relation \ref{eq1} and eq.A.9, the previous expression equals

$$E_t^1 \left[\frac{U'(c_{t+1})}{U'(c_t)} y_t \right] = E_t^1 \left[\frac{\beta W_t}{\beta W_{t+1}} y_t \right] = E_t^1 \left[\frac{\beta W_t}{\beta W_{t+1}} \frac{W_{t+1}}{W_t} X_t \right] = E_t^1 \left[X_t \right] \tag{A.11}$$

Then, for agent 2,

$$P(y_t) = E_t^2 \left[\frac{U'(c_{t+1})}{U'(c_t)} y_t \right] = E_t^2 \left[\frac{c_t}{c_{t+1}} y_t \right] = E_t^2 \left[\frac{W_t}{W_{t+1}} \frac{W_{t+1}^1}{W_t^1} X_t \right] = E_t^2 \left[\frac{\eta_t}{\eta_{t+1}} X_t \right] \tag{A.12}$$

where $\eta_t = \frac{W_t^2}{W_t^1}$, that is, the relative wealth of country 2 with respect to country 1.

Since in an integrated market the price of the asset should be the same (no arbitrage), then we find the relationship between the probability measure of country \$1\$ and country 2, that is

$$E_t^1[X_t] = E_t^2\left[\frac{\eta_t}{\eta_{t+1}}X_t\right] \tag{A.13}$$

See that the ratio of probabilities assigned by these groups to different states is perfectly correlated with their wealth ratios, being the logarithmic utility function assumption the cause of this simplified result.

Under the usual homogeneous agent models there is a unique stochastic discount factor (*SDF*). Due to the logarithmic utility function, the *SDF* is inversely related to their aggregate wealth:

$$\frac{M_t^H}{M_t^0} = \beta\frac{U'(c_t)}{U'(c_0)} = \beta\frac{c_0}{c_t} = \beta\frac{W_0}{W_t} \tag{A.14}$$

where H stands for homogeneous economy, meaning an economy where only agent type 1 or 2 is present, that is, a perfectly segmented market for the developed and the emerging.

Under the no arbitrage condition and using the type 2 probability measure, the following relationship holds (see proof below):

$$\frac{M_t^2}{M_t^2} = \left(\omega_0^1\frac{\eta_t}{\eta_0} + \omega_0^2\right)\frac{M_t^H}{M_t^H} \tag{A.15}$$

At t, an asset with a expected payoff X_{t+1} has a price P_t:

$$P_t = E_t^2\left[\frac{M_{t+1}}{M_t}X_{t+1}\right] = E_t^2\left[\beta\frac{W_t}{W_{t+1}}\left(\omega_t^1\frac{\eta_{t+1}}{\eta_t} + \omega_t^2\right)X_{t+1}\right] \tag{A.16}$$

By equation , and substituting in the previous expression,

$$P_t = \omega_t^1\beta E_t^1\left[\frac{W_t}{W_{t+1}}X_{t+1}\right] + \omega_t^2\beta E_t^2\left[\frac{W_t}{W_{t+1}}X_{t+1}\right] \tag{A.17}$$

Then

$$P_t = \omega_t^1 E_t^1 \left[\frac{M_{t+1}^H}{M_t^H} X_{t+1} \right] + \omega_t^2 \beta E_t^2 \left[\frac{M_{t+1}^H}{M_t^H} X_{t+1} \right] = \omega_t^1 P_t^1 + \omega_t^2 P_t^2 \tag{A.18}$$

where $P_t^i = E_t^i \left[\frac{M_{t+1}^H}{M_t^H} X_{t+1} \right]$ is the price of the asset of an homogeneous economy in which only group-i agents are present.

Applying the definition of covariance ,

$$P_t = \omega_t^1 \left[cov \left(\frac{M_{t+1}^H}{M_t^H}, X_{t+1} \right) + E_t^1 \left(\frac{M_{t+1}^H}{M_t^H} \right) E_t^1 (X_{t+1}) \right] \tag{A.19}$$

$$+\omega_t^2 \left[cov \left(\frac{M_{t+1}^H}{M_t^H}, X_{t+1} \right) + E_t^2 \left(\frac{M_{t+1}^H}{M_t^H} \right) E_t^2 (X_{t+1}) \right] \tag{A.20}$$

Define $m_{t+1} = \frac{M_{t+1}^H}{M_t^H}$. Then, for simplicity, suppose that,
$a) cov\left(m_{t+1}^1, X_{t+1}\right) = cov\left(m_{t+1}^2, X_{t+1}\right) = \phi$
$b) E_t^1\left(X_{t+1}\right) = E_t^2\left(X_{t+1}\right) = \chi$

Substituting in equation A.19 the expression for the asset price reduces to

$$P_t = \omega_t^1 \left[\phi + E_t^1 (m_{t+1}) \chi \right] + \omega_t^2 \left[\phi + E_t^2 (m_{t+1}) \chi \right] \tag{A.21}$$

The expression encloses a weighted average of the idiosyncratic *SDF*, where the weights are the relative wealths. To have a clearer sight at the expression, set $\phi = 0$ and $\chi = 1$. In this case, equation A.21 reduces to:

$$P_t = \omega_t^1 \left[E_t^1 (m_{t+1}) \right] + \omega_t^2 \left[E_t^2 (m_{t+1}) \right] \tag{A.22}$$

Assuming type 1 is the developed country, and type 2 the emerging one, then the weight on the developed country is much higher than the weight on the emerging one, so the *SDF* of the developed market weights much more than the *SDF* of the emerging one.

Note that the *SDF* already incorporates all available information on future income, labor income, consumption and all other type of shocks, plus the preferences on how to deal with them (although in this exercise I assumed same utility function for both types). In the context of this paper, the former expression implies that the expected changes in the US business cycle should be relevant in an integrated financial system as the sovereign debt market is.

Proof of Lemma 1

Lemma 1: Under the no arbitrage condition and using the type 2 probability measure, the following relationship holds:

$$\frac{M_t^2}{M_t^2} = \left(\omega_0^1 \frac{\eta_t}{\eta_0} + \omega_0^2\right) \frac{M_t^H}{M_t^H} \tag{A.23}$$

`Demonstration`

$$c_t^2 = \beta W_t^2 = \frac{W_t^2}{W_t} \beta W_t = \beta W_t \frac{1}{\frac{W_t^1 + W_t^2}{W_t^2}} = \beta W_t \frac{1}{1+\eta}$$

where $W_t = W_t^1 + W_t^2$ and $\eta = \frac{W_t^1}{W_t^2}$

The *SDF* for type 2 is then:

$$\frac{M_t}{M_0} = \beta \frac{U'(c_t)}{U'(c_0)} = \beta \frac{c_0}{c_t} = \beta \frac{W_0}{W_{t+1}} \frac{\frac{1}{1+\eta_0}}{\frac{1}{1+\eta_t}} = \beta \frac{W_0}{W_t} \frac{1+\eta_t}{1+\eta_0} =$$
$$\beta \frac{W_0}{W_{t+1}} \left(\frac{1+\eta_t}{1+\eta_o} + \frac{1}{1+\eta_0}\right) = \beta \frac{W_0}{W_t} \left(\omega_0^1 \frac{\eta_t}{\eta_0} + \omega_0^2\right)$$

since we are working with type 2, the homogeneous economy *SDF* is

$$\frac{M_t}{M_0} = \beta \frac{W_0}{W_t} = \frac{M_t^H}{M_0^H}$$

then the previous expression is rephrased as

$$\frac{M_t}{M_0} = \frac{M_t^H}{M_0^H} \left(\omega_0^1 \frac{\eta_t}{\eta_0} + \omega_0^2\right)$$

APPENDIX V.2 PRINCIPAL COMPONENTS ANALYSIS

The first to apply Principal Components Analysis (PCA) to financial data were Litterman and Scheinkman (1991). More specifically, they calculated the first three principal components, from the excess returns (over the overnight interest rate) for U.S. bonds for different maturities up to 30-year bond. They named the first factor level, the second factor steepness and the third curvature. This paper has been very influential in the subsequent literature on term structure curve models and these latent factors have become standards.

The PCA technique has been applied to different financial asset classes. More specifically, PCA has been applied to U.S. Treasury bond yield spreads, swap rates, stock returns, corporate spreads, exchange rates, derivatives, emerging stock market returns and emerging market sovereign spreads. Specially relevant for this work are the papers where PCA is applied to corporate spreads and emerging market sovereign spreads: Kennedy and Slot (2004) for corporate spreads, and Avellaneda and Scherer (2000); Cifarelli and Paladino (2002) and Kennedy and Slot (2004) for emerging market spreads.

By exploiting the potential information redundancy in multivariate data sets, PCA is applied with the aim of identifying the pattern of comovements reducing the dimensionality of the data, in a way to minimize the loss of information. This is achieved by projecting the data onto fewer dimensions, so that the maximum amount of information, measured in terms of variability, is retained in the smaller number of dimensions. In this way PCA transforms a set of p correlated variables into a smaller subset of m uncorrelated variables (principal components) that are orthogonal linear combinations of the original ones.

The data set, in this case, time series for spreads (can be enlarged to stock markets, interest rates, etc), can be represented by an $Nx1$ column vector

$$Y_t = [y_t^{(1)}, y_t^{(2)}, ..., y_t^{(N)}]'$$

where each $y_t^{(i)}$ is the spread on sovereign bonds issued by an emerging market debtor country. Let $\overline{Y} = [\overline{y}(1), \overline{y}(2), ..., \overline{y}(N)]'$ be the vector of sample means and $\sum(s_{ij})$ be the NxN sample covariance matrix.

Then the principal component transformation of the random vector Y_t is

$$Y_t \longrightarrow Z_t = \Gamma'(Y_t - \overline{Y})$$

where Γ is a NxN orthogonal matrix whose ith column γ_i is the ith eigenvector of Σ. It is also called the ith vector of principal components loadings.

$\Gamma'\Sigma\Gamma = \Lambda$ is diagonal with ordered entries $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \lambda_N$. Z_t is a $Nx1$ vector of principal components, where the ith principal component $z_t^{(i)}$,

$$z_t^{(i)} = \gamma_i'[Y_t - \overline{Y}]$$

has zero mean and variance λ_i (the ith eigenvalue of Σ).

The latter, appropriately normalized, allows to measure the fraction of the variance of the original data explained by the ith principal component. In the same way, the sum of the first k normalized eigenvalues indicates how much of the variation is explained by the first k principal components. The first principal component $z_t^{(1)}$ is the linear combination of the original variables, obtained using as loadings the entries of vector γ_t', which has maximum variance among all the (standardized) linear combinations of Y_t ; the second principal component $z_t^{(2)}$ is the linear combination, among all standardized linear combinations of Y_t uncorrelated with the first principal component, with the largest variance and so on. An interesting property of the PCA is that the equation

$$Y_t \longrightarrow Z_t = \Gamma'(Y_t - \overline{Y})$$

can be inverted so that the original variables may be stated as a function of principal components as $Y_t = \overline{Y} + \Gamma Z_t$ where, Γ being orthogonal, $\Gamma^{-1} = \Gamma'$. The principal components loadings thus provide a measure of the relative change in the value of the spreads in Y_t response to a shock in a principal component.

My approach will be different than that of **?** and **?**, in the sense that I will not set rolling windows to extract the first (second and third) principal components, and then check for time variations in their relative importance. My approach will consist in extract a time series data from the original data set, in a way that the vector corresponds to the first principal component projection, and so on. As usual in the literature, this projection of the data matrix onto the eigenvector corresponding to the higher eigenvalue is understood as the global investment appetite time series.

The projection of the data matrix onto the j principal component related vector is just

$$PC_t^j = z_t^{(1)}.Y_t'$$

In choosing how many principal components to use, two common rules of thumb are usually employed. The first uses only those components that have eigenvalues greater than one (Kaiser criterion); while the second, includes enough factors to explain 80 to 90\% of the variation (variance-explained criterion).

Principal Component Analysis

The results indicate the high importance of the first principal component in explaining the common variance. For the EMBI+ sample, the proportion of variance accounted for by the first principal component is around 57% (stationary case). For the USC sample, the first principal component explains 68.4%. According to **?** a value in the 65-80% range would correspond to a regime of ”strong movement”[9], characterized by a high degree of correlation in the aggregate movement of spreads. As **?** point out, this thresholds are optimal for an analysis based on the covariance matrix, but not useful for the correlation method because this method standardizes the original spreads before computing the principal components; the influence of extreme observations is significantly reduced[10] . Thus, in their paper the authors use the following thresholds: *i*) Extreme Coupling: Percentage of variance explained by first principal component is above 50%. *ii*) Strong Coupling: Percentage of variance explained by first principal component is between 35-50%. *iii*) Weak Coupling: Percentage of variance explained by first principal component is below 35%. In either case, our results imply very high coupling. As initially suspected, the explained proportion of the variance decreases if the analysis is corrected by stationarity, but even in this case, we are in a extreme coupling scenario.

[9]For the covariance method, the authors proposed the following categories: 1) Extreme Coupling: Percentage of variance explained by first principal component is above 80%; 2) Strong Coupling: Percentage of variance explained by first principal component is between 65-80% and 3) Weak Coupling: Percentage of variance explained by first principal component is below 65%.

[10]The authors put the following example: think of a sample of observations where one variable has a large variance (say, variable 1) and the other variables have a small variance. In this case the first principal component will be almost perfectly correlated with variable , and at the same time will explain almost all the variance. If we reduce the variance of variable and increase the variance of the other variables, the percentage of variance explained by variable will decrease (and also its correlation with the first component). This is the effect produced by standardizing the variables. Summing up, for the same sample of observations, the first component will explain a lower percentage of the variance and, thus, we need to reduce the thresholds for classifying different episodes.

APPENDIX V.3 FAMA-FRENCH FACTORS AS PROXY FOR INNOVATIONS

I repeat the exercise for Petkova (2006) using the same beginning of the time series she uses. The results again do not match the results of Petkova, in relation to the significant relationship between the innovation to $TERM_t$ and the HML FF factor, and between the innovation to DEF_t and the SMB FF factor. Again, I am using the dividend yield ratio from Schiller, not the data for dividend yield that the author uses. However, this time a significant relationship between the innovation to $TERM_t$ and the HML Fama French factor is found, but not between the innovation to DEF_t and the SMB FF factor.

Table A: Orthogonalized innovations on MKT and FF factors. Sample 1963-2006.

Notes: The variables $\hat{u}_t^{DIV}$; $\hat{u}_t^{TERM}$; $\hat{u}_t^{DEF}$ and $\hat{u}_t^{Rf}$ stand for the dividend-yield ratio innovation, the term spread innovation, the default spread innovation, the risk free rate innovation (respectively), ortoghonalized with respect to the market excess return. $\hat{u}_t^{HML}$ and $\hat{u}_t^{SMB}$ stand for the Fama French factor innovations, ortoghonalized with respect to the market excess return. The US Fama French factors are the market excess return (MKT), the small minus big capitalization return (SMB) and the high minus low book to market value return (HML). The series are from French's webpage. The t-statistics are inside parenthesis, and corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags. Significance levels reported: * 10%, ** 5%, *** 1%. The adjusted R^2s from each regression are reported in percentage form. The sample period is from February 1963 to December 2006.

	$\hat{u}_t^{DIV}$	$\hat{u}_t^{TERM}$	$\hat{u}_t^{DEF}$	$\hat{u}_t^{Rf}$	$\hat{u}_t^{SMB}$	$\hat{u}_t^{HML}$
MKT	0.00081	0.01140	0.00826	-0.00397	-0.29090***	0.40276***
	(0.21193)	(0.57096)	(0.63340)	(-0.20040)	(-22.54197)	(50.30515)
SMB	0.00199	0.00962	-0.00832	-0.01934	0.93343***	-0.01233
	(0.58576)	(0.89888)	(-0.83540)	(-1.449764)	(58.3222)	(-1.446607)
HML	0.00343	0.03482**	0.01401	-0.02383	-0.02532	0.97170***
	(1.19840)	(2.08440)	(1.16804)	(-1.33376)	(-1.57770)	(100.6251)
Cte	0.00012	0.00078	-0.00028	-0.00117	0.04610***	0.00798
	(0.06167)	(0.06560)	(-0.02739)	(-0.10176)	(3.33736)	(0.82963)
Adj. R^2	0.16333	1.04472	0.08522	0.23861	93.18364	96.6933
N	527	527	527	527	527	527

Table B: Using innovations on factors (1963-2006)

Notes: The t-statistics are inside parenthesis, and corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags. Significance levels reported: * 10%, ** 5%, *** 1%. The adjusted R^2s from each regression are reported in percentage form. The sample period is from February 1963 to December 2006.

	EMBI+	Arg	Bra	Mex	Per	Ven	Ecu	Pan	Bul	Mor	Nig	Pol	Rus
MKT	-0.00783***	-0.01079*	-0.01010***	-0.00861***	-0.00668***	-0.01446***	-0.00712**	-0.00837***	-0.01008***	-0.01002***	-0.01215***	-0.00877***	-0.00533
$\hat{u}_t^{DIV}$	-0.30111***	0.03272	-0.36038**	-0.33428***	-0.37612***	0.05766	-0.23952	-0.16727	-0.17604*	-0.17877	-0.27938	-0.30253**	-0.52543***
$\hat{u}_t^{TERM}$	0.01120	0.22021	0.04469	-0.00966	0.00310	0.05488	0.05709	-0.01065	0.00998	0.06381	-0.19100***	-0.13232**	0.00220
$\hat{u}_t^{DEF}$	-0.07212	0.10202	-0.019435	-0.05010	-0.04930	-0.01479	-0.06567	-0.05109	-0.07867	-0.05677	-0.08904	-0.04948	-0.11618*
$\hat{u}_t^{Rf}$	0.07192	0.21708	0.09336*	0.00229	0.05543	0.22477**	0.10011	0.06114	0.14033*	0.091280	0.13172	0.05315	-0.01730
C	-0.00505	-0.00338	-0.00495	-0.00885	-0.00791	-0.00045	0.00314	-0.000137	-0.01441	-0.01129	0.00470	-0.00955	-0.01346
Adj. R^2	26.69	2.89	24.34	30.53	14.97	24.48	4.59	30.34	20.83	10.02	24.55	14.30	12.51
N	97	97	97	97	97	97	97	97	97	97	97	97	97

Table C: Emerging Stock Market Real Excess Returns and US Fama French Factors

The t-statistics are inside parenthesis, and corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags. Significance levels reported: * 10%, ** 5%, *** 1%. The adjusted R^2s from each regression are reported in percentage form. The sample period is from February 1963 to December 2006.

	Bra	Mex	Chi	Col	Per	Ind	Phi	Tha
MKT	0.1797213***	0.1113088***	0.0473215***	0.1939076***	0.1300288***	0.1731159**	45.46109	0.221195*
SMB	0.0082514	0.0582413**	0.0511227***	0.1364268***	0.0318503	0.1125856*	73.85405	-0.0138896
HML	-0.1030633	-0.04989*	0.052495**	0.2186941**	0.0542603	0.123183	90.01538	0.0388961
C	0.8869989***	0.4775968***	0.1483106**	0.7573314***	0.6593719***	0.6383861***	145.4977	0.8119258**
Adj.R^2	47.89	54.15	14.88	12.20	14.51	19.99	3.06	12.19
N	107	107	107	107	107	107	107	107

	Mal	Kor	Ind	Pak	Chi	Egy	SAU	ZFA
MKT	0.0937052	0.134121**	0.0370176*	0.0518175	0.1394333***	0.0190323	0.0212731	0.0626109***
SMB	0.0861447*	0.0493729	0.0659821***	0.1100608***	0.0294215	-0.0012432	0.0677149**	0.0422317***
HML	0.0650846	-0.0137528	0.0327804	0.0556502	0.020407	-0.0039861	0.044046	0.0410166**
C	0.4204044**	0.7133998**	0.3693497***	0.4702537***	0.3623701**	0.2495995***	0.5032351***	0.2217797***
Adj.R^2	14.26	18.59	11.83	6.06	36.10	0.02	3.07	20.22
N	107	107	106	107	107	107	107	107

APPENDIX V.4 FORMAL ASSET PRICING MODEL TESTS

Formal Asset Pricing Model Tests: Theory Review

In this subsection I go beyond the coefficient significance and the adjusted R^2s of the regressions, and set the formal statistics in order to reject or not an asset-pricing model. I present formal statistics to both the time series and cross-sectional regressions in order to check if the US Fama French factors constitute a good asset-pricing model for Emerging Markets sovereign debt returns.

For the time series analysis, the literature focus on the Gibbons, Ross and Shanken (1989) statistic (GRS). The statistic has a finite-sample F distribution for the hypothesis that a set of parameters are jointly zero, parameters that in this case are the αs or constants. For the cross-sectional, I report another statistic that also distributes F after adjusted for small sample bias and for the estimated betas bias (Shankan (1992) correction).

With many factors, for the time series analysis we have multiple regressions of the type:

$$R^e_{jt} = \alpha_j + \beta_j' f_t + \varepsilon_{jt}$$

The model states that expected returns are linear in multiple betas,

$$E(R^e_j) = \beta_j' E(f)$$

Assuming i.i.d. errors, the GRS (1989) statistic takes the following form (Cochrane, 2005 and Singleton, 2006)

$$\tfrac{T-N-K}{N}\left[1 + E_T(f)'\hat{\Omega}^{-1}E_T(f)\right]^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha} \approx F(N, T-N-K)$$

where N is the number of assets, K is the number of factors and $\hat{\Omega}$ is:

$$\hat{\Omega} = \tfrac{1}{T}\sum_{t=1}^{T}[f_t - E_T(f)][f_t - E_T(f)]'$$

The cross-sectional regressions start with the K factor model $E(R_j^e) = \beta_j'\lambda$ where $j = 1,2,...,N$, and where factors are excess returns. The two-pass regression estimation is done by firstly doing time-series regressions, and then estimating the factor risk premia λ from a cross-sectional regression of average returns on the betas,

$$E_T(R_j^e) = \beta_j'\lambda + \varepsilon_j \quad , j = 1,2,....,N$$

The betas are the explanatory variables, λ are the regression coefficients, and the cross-sectional regression residuals ε_j are the pricing errors. See that the theory says that the constant or zero-beta excess return should be zero, which is the joint hypothesis to be tested. Since the residuals in the cross-sectional regression are correlated with each other, I run a GLS cross-sectional regression. Taking into account Shanken's correction (1992) for estimated betas, the asymptotic statistic to test the hypothesis is

$$T\left(1+\lambda'\Sigma_f^{-1}\lambda\right)\hat{\varepsilon}_{GLS}'\Sigma^{-1}\hat{\varepsilon}_{GLS} \approx \chi^2(N-K)$$

The small sample correction comes from the fact that the previous statistic with an estimated $\hat{\Sigma}$ is exactly distributed in finite samples as a Hotelling T^2 distribution. Letting $Q = T'\hat{\varepsilon}'\hat{\Sigma}^{-1}\hat{\varepsilon}$, since the square of a t-distribution is a F-distribution, it can be shown that

$$F = \tfrac{Q(T-N+K)}{(N-K)(T-K)}$$

has a F-distribution in small samples with $N-K$ and $T-N+K$ degrees of freedom. I do not do Fama-Macbeth procedure because I do not have enough data for the rolling 5-year correlations generally used in the procedure.